Off-exchange trading and post earnings announcement drift

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Abstract

Off-exchange trading, which tends to attract uninformed trades, accounts for 34 percent of trading volume today. Microstructure theory suggests that taking uninformed trades off exchanges harms liquidity but improves price discovery prior to public disclosure. We examine how this trade-off affects a longstanding anomaly suggesting that investors underreact to earnings news. Arbitrageurs are unable to fully correct this mispricing because of various costs. The liquidity (price discovery) channel predicts that off-exchange trading increases (decreases) underreaction. Our results, based on a large panel of US firms and a natural experiment created by the SEC's Tick Size Pilot program, suggest the liquidity channel dominates. The negative effects of off-exchange trading on liquidity (less depth and wider spreads) likely increase arbitrage costs, thereby increasing residual underreaction. Our results also suggest that research can use levels of off-exchange trading to proxy for hard-to-measure arbitrage costs.

Keywords: Off-exchange trading; Post-earnings-announcement-drift; Limits to arbitrage; Liquidity; Price discovery; Price efficiency.

Online appendix:
https://drive.google.com/file/d/1weM_Ic1qNoT46JuvWOy1BRdDKxt_4hCJ/view?usp=sharing

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1. Introduction

Off-exchange trading (OFFEXCH) has increased over the past 20 years and now accounts for about 34 percent of total U.S. trading volume. Unlike "lit" exchanges, OFFEXCH is referred to as dark trading because investors are unaware of submitted orders until executed. Take crossing networks for example: buy and sell orders are not visible to market participants; if matched they are recorded on the consolidated tape, and unmatched orders are returned. Two concurrent studies, Balakrishnan and Taori (2017) and Gkougkousi and Landsman (2018), show that OFFEXCH increases around earnings announcements. Regulators and accountants are interested in a related, but different, question: does the choice between lit and dark venues affect the process by which information, private and public, is incorporated into stock price?[1] To investigate this question, we examine the impact of OFFEXCH on a longstanding anomaly known as PEAD: investor underreaction to quarterly earnings, indicated by price drifts after earnings announcements (Joy et al. 1977).[2]

OFFEXCH is linked to PEAD because it segments uninformed and informed order flows. As explained below, uninformed trades either gravitate toward or are channeled to dark venues (e.g. Menkveld, et al. 2017). Liquidity providers on exchanges then face higher odds of trading against private information. Theory (e.g., Hendershott and Mendelson, 2000; Zhu, 2014) predicts a decline in liquidity, indicated by wider bid/ask spreads and less depth of unfilled limit orders. We confirm that prediction empirically using more comprehensive analyses than those conducted

[1] For example, Mary Jo White (former SEC Chairman) expresses concerns about increases in OFFEXCH, and suggests it may have reached a level that "*risks seriously undermining the quality of price discovery provided by lit venues.*"

[2] We do not study the other well-documented accounting anomaly—overreaction to the accrual component of earnings (Sloan, 1996)—because it is muted in our sample. Also, microstructure frictions that vary strongly with OFFEXCH (see below) have been shown in prior research to vary with PEAD, but not the accrual anomaly.

in prior work (e.g., O'Hara and Ye 2011, Hatheway et al. 2017, Farley et al. 2018, SEC 2018), which has shown mixed results. As higher transaction costs reduce the ability of arbitrageurs to fully correct underreaction to earnings news (Bhushan 1994, Ng et al. 2008, and Chordia et al. 2009), this liquidity channel predicts a positive relation between OFFEXCH and PEAD.

On the other hand, removing uninformed trades off exchanges increases the signal-to-noise ratio of stock prices, which enhances price discovery *prior to* scheduled releases of public information[3]. Empirically, Brogaard and Pan (2018) show that OFFEXCH volume on two dark venues increases price discovery prior to earnings announcements. If stock prices reflect more earnings news before it is announced, there is less room for subsequent price responses (Vega, 2006), resulting in less underreaction. The price discovery channel thus predicts that OFFEXCH is negatively related to PEAD because it increases price discovery.[4] We investigate whether this negative relation is offset by the positive relation predicted by the liquidity channel.

We begin with research findings regarding two relevant background questions. First, why are uninformed (informed) orders segmented to dark venues (lit exchanges)? Segmentation occurs for different reasons for institutional and retail orders. Institutional orders sent to dark pools benefit from price improvement at the expense of immediacy. Price improvement occurs because buys/sells are filled within the spread, but immediacy is compromised because execution is not assured. Unlike uninformed trades that are patient and value price improvement over immediacy, informed trades value the immediacy offered by exchanges (e.g., Menkveld et al. 2017). Moreover, informed trades are less likely to be matched on dark venues because they are positively correlated

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[3] Following Zhu (2014), price discovery is the process by which private information is incorporated into stock price ahead of it becoming publicly available.

[4] Support for a positive link between OFFEXCH and improved signal-to-noise ratios and price discovery is also provided by results in the Finance literature (which we confirm in our sample) suggesting that OFFEXCH reduces intraday inefficiency, or deviation of intraday price changes from a random walk.

and likely to accumulate on the same "heavy" side of the market (Zhu 2014). In contrast, uninformed orders are more evenly distributed.

Turning to retail orders, segmentation is an outcome of "cream-skimming," not investor choice. Almost all marketable orders received by brokers from individual investors are either purchased by unaffiliated OTC market makers or routed to affiliated OTC market makers for execution (Battalio et al. 2016; SEC, 2010). OTC market makers internalize uninformed orders, and route to exchanges any orders they suspect are informed (e.g., Easley et al. 1996).

Second, how does PEAD arise and is there evidence connecting it to the two competing channels? Prior research suggests it reflects the net effect of two types of traders. Noise traders do not appreciate fully the positive autocorrelation in seasonally-differenced quarterly earnings (e.g., Bernard and Thomas, 1990), causing prices to underreact. Arbitrageurs then trade in the direction of earnings news, to profit from this mispricing, but their incentives to do so decline as mispricing drops to levels corresponding to the sum of various arbitrage costs they face (Lee and So, 2015; Ng et al. 2008). Consistent with arbitrage costs creating the positive OFFEXCH/PEAD relation predicted by the liquidity channel, prior evidence suggests that magnitudes of PEAD vary in the cross-section with proxies for various costs of executing arbitrage strategies (Bhushan 1994, Ng et al. 2008, and Chordia et al. 2009). Consistent with the negative OFFEXCH/PEAD relation predicted by the price discovery channel, Vega (2006) finds lower PEAD when the probability of informed trading (Easley et al. 1996) in the pre-announcement window is high.

To test the relation between OFFEXCH and PEAD, we use a comprehensive sample that includes all US firms with daily TAQ data from 2009 to 2018. Our sample of 82,502 firm-quarters yields the following descriptive findings. First, average OFFEXCH increases from about 25 percent of overall trading to about 34 percent over our sample period. Notwithstanding this increase over time, OFFEXCH is relatively sticky: it exhibits little within-firm variation both across days within quarters and across quarters. Second, OFFEXCH is related in the cross-section to arbitrage cost proxies from prior work: It varies positively with idiosyncratic return volatility (Mendenhall, 2004), and varies negatively with market capitalization (Foster, Olsen, and Shevlin, 1984) and liquidity (Ng et al. 2008)—measured by intraday effective spread and depth at national best bid and ask prices (NBBO).

Whereas the prior evidence is clear that OFFEXCH improves price discovery (Brogaard and Pan 2018), it is mixed about the impact of OFFEXCH on liquidity. As described further in Section 2.3.2, these differences might be due to prior studies using small samples and narrow windows around changes in OFFEXCH. Given that the liquidity channel relies on the negative relation between OFFEXCH and liquidity predicted by theory, we first investigate if that negative relation is observed for our sample. We also use a natural experiment created by the SEC's Tick Size Pilot Program of 2016 to alleviate potential concerns about endogeneity affecting our main sample results. We estimate difference-in-difference regressions on two groups of small capitalization stocks over the two-year periods before and after the change imposed by the SEC program. The incentive to trade off exchanges declines substantially for one group (treatment) but increases for the other (control). Our results are unequivocal: For both the main and Tick Size Pilot samples, OFFEXCH is negatively associated with liquidity, measured by intraday effective spread and depth at NBBO. Observing the same negative association for the natural experiment suggests a causal impact.

We next turn to investigate the question of interest: is OFFEXCH positively or negatively related to PEAD? We follow recent studies (e.g. Milian 2015) and define earnings news as earnings announcement returns and analyst forecast error.[5] We find that OFFEXCH exhibits a statistically and economically significant *positive* relation with PEAD for our main sample, and this relation is observed for both our long and short positions. The results suggest that the increased underreaction due to the liquidity channel is stronger than the reduction due to the price discovery channel. To illustrate economic significance, a hedge portfolio that invests long (short) in the quintile of firms with the best (worst) earnings news generates close to zero returns over the next quarter for the lowest OFFEXCH quintile but earns almost 8 percent for the highest quintile.

We return to the natural experiment created by the Tick Size Pilot to extend our main sample results. We find a similar, significant positive relation between OFFEXCH and PEAD when earnings news is measured as announcement returns, but the relation is not significant when earnings news is measured as forecast errors. This latter result is due to PEAD for our Tick Size sample being strong and significant when earnings news is measured as announcement returns, but insignificant for forecast errors. If PEAD is at the outset insignificant for forecast errors, it is not surprising that variation in PEAD with OFFEXCH is also insignificant. This result is in line with the emerging consensus that announcement returns are a better measure of earnings news (e.g., Milian 2015).[6]

Consistent with the liquidity channel, we find that the positive relation between OFFEXCH and PEAD declines as we control for various arbitrage cost proxies. This result reinforces the view that observed PEAD reflects limits to arbitrage (e.g., Bhushan 1994; Ng et al. 2008; Chordia et al. 2009): underreaction by noise traders is corrected to the point where mispricing equals arbitrage

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[5] Early PEAD research measures earnings surprise as seasonally-differenced quarterly earnings (SUE). However, the ability of SUE to predict PEAD has declined in recent years.

[6] Perhaps forecast errors are subject to increasing manipulation, and levels of manipulation vary across firms. For example, Cheong and Thomas (2017) show systematic cross-sectional variation in mean forecast errors, generated by variation in forecast guidance designed to generate positive forecast errors.

costs. However, a substantial fraction of the OFFEXCH/PEAD relation remains despite controls for a host of observable arbitrage cost measures. The incremental ability of OFFEXCH to explain underreaction suggests two possibilities: (a) observable arbitrage cost measures widely used in the literature, capture actual costs paid by arbitrageurs with error (e.g. Jones and Lipson 2001); and (b) OFFEXCH proxies for unobservable arbitrage costs, such as the costs of arbitrage capital (Lee and So, 2015). Regardless, OFFEXCH is a useful proxy for hard-to-measure arbitrage costs.

This paper contributes to two literatures. We extend the PEAD literature by showing that PEAD increases with off-exchange trading. Recent increases in OFFEXCH raise the importance of this unexplored source of variation in PEAD. Finding that the liquidity effect is important confirms the key role of arbitrage costs. Our results also suggest that arbitrage costs extend beyond the costs of trading considered in prior research (Lee and So, 2015). At a methodology level, we offer an additional proxy for arbitrage costs—levels of OFFEXCH—that should be useful for researchers investigating pricing anomalies.

We contribute to the general OFFEXCH literature by investigating a comprehensive panel of US firms since 2009 as well as a natural experiment created by the SEC's Tick Size Pilot program. We confirm the theoretical prediction that off-exchange trading harms liquidity in U.S. markets, and find that this negative liquidity effect exacerbates investor underreaction to earnings news. While increased mispricing of public disclosures should concern regulators, we recognize that OFFEXCH may have offsetting beneficial effects. For example, it improves price discovery ahead of public announcements (e.g., Brogaard and Pan 2018), and it improves price discovery in intraday trading (our untabulated results).

The remainder of this paper is laid out as follows. Section 2 details the institutional setting, describes the prior literature and develops our empirical prediction. Section 3 provides details of our sample selection process and some descriptive statistics. Section 4 presents our main results. Section 5 contains robustness checks, and Section 6 concludes.

2. Institutional setting, prior literature, and predictions.

2.1. Structure of trading markets for equity.

As accounting audiences may be less familiar with recent innovations in dark trading, we take this opportunity to describe different trading venues and review prior research linking institutional features of dark venues to liquidity and price discovery. We provide a brief history of off-exchange trading in Section A5 of the Online Appendix.

The stock market in the U.S. offers both lit and dark trading venues. Lit venues—primarily registered exchanges—provide both pre and post-trade transparency. Prices and trading interests are displayed prior to execution, and transaction details are publicly disseminated in real time.[7] Registered exchanges are generally structured as electronic limit order book markets, where multiple buyers and sellers can trade against each other within the system. They offer nondiscriminatory access, and operate according to nondiscretionary rules and procedures.[8]

Dark venues, on the other hand, provide post-trade transparency but are pre-trade opaque: their best priced bids and offers are not required for inclusion in publicly distributed, consolidated quotation data. Transaction prices in dark venues are typically derived from or pegged to NBBO on exchanges. In addition, dark venues are not subject to fair access requirements, and can thus prohibit or limit clients from accessing their services. The SEC (e.g., Concept Release 34-61358, 2010) and the finance literature (e.g. Zhu 2014; Buti, Rindi, and Werner 2017) divide dark venues

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7 Exchanges do permit hidden limit orders, which are not pre-trade transparent.

8 Electronic communication networks (ECN) are similar to exchanges, except they do not provide all services provided by exchanges, such as stock listings. As of March 2012, there is only one significant ECN–LavaFlow– which only accounts for around 2 percent of the consolidated share volume (CFA Institute, 2012).

into four major groups, based on trading mechanisms employed.

(1) **Crossing networks** (e.g., ITG Posit). Customers in crossing networks, mainly buy-side institutions, submit unpriced orders. At prescheduled times, the organizing agency brokers—who do not trade on their own account—match buy and sell orders at “intermediate” prices derived from lit venues, such as the midpoint between national best bid and offer prices (NBBO) and volume-weighted average price (VWAP). Imbalances in buy and sell orders remain unfilled. Crossing networks provide price improvement at the expense of immediacy, consistent with anecdotal evidence suggesting that they were initially designed for block trades (Kwan et al. 2015).

(2) **Nondisplayed limit order book** (e.g., GS Sigma X). Nondisplayed limit order books (LOB hereafter) are limit order books without pre-trade transparency. These nondisplayed LOBs are usually operated by banks or brokers, who also trade on their own accounts. Customers are again mainly buy-side institutions who can submit market, limit, or pegged orders[9]. Execution prices are derived on a continuous basis from the prices of submitted orders, typically bounded by NBBO on exchanges. These venues provide more immediacy than crossing networks, but offer less price improvement.

(3) **PING destinations** (e.g., Knight Link). PING venues are fast electronic market makers that immediately accept or reject incoming orders. These PING venues are usually operated by over-the-counter (OTC) market makers, who trade as principals. Their main customers are buy-side institutions who submit immediate or cancel (IOC) orders. Execution prices are determined by market makers. PING venues also provide more immediacy than crossing networks, but offer less price improvement.

(4) **Broker/dealer internalization** (e.g., Citadel securities). Broker/dealer internalization refers to OTC market makers purchasing *retail* order flow from brokerage firms and executing it internally. Battalio et al. (2016) show that almost all retail marketable (i.e. market or marketable limit) orders and half of all retail limit orders are routed by retail brokerages directly to OTC wholesale dealers. Knowledge of the identities of the retail orders allows OTC market makers to internalize uninformed retail flow and route potentially informed flow to exchanges. When internalizing retail orders, OTC market makers often provide retail investors with little (e.g. $0.001) or no price improvement relative to NBBO.

Using proprietary data from NASDAQ in 2010-2011, Kwan et al. (2015) and Menkveld et al. (2017) estimate that the fraction of overall trading volume executed on crossing networks, nondisplayed LOBs, PING venues, and broker/dealer internalization is around 2.5 percent, between 7.8 to 9.8 percent, between 4.5 to 7.8 percent, and between 5.7 to 12.9 percent, respectively. The four dark venues are subject to different regulatory oversight. Crossing networks

[9] Pegged orders are limit orders with the limit price set relative to an observable market price, such as the bid, the offer, or the midpoint. The limit price of pegged orders moves with the market (Zhu 2014 online appendix).

and nondisplayed LOBs operate as alternative trading systems (ATS) and need to comply with Regulation ATS, while PING venues and retail internalization are registered as non-ATS market makers subject to broker-dealer regulations.

2.2. The post-earnings announcement drift (PEAD)

Price drifts after earnings announcements have been documented first for annual earnings (Ball and Brown, 1968) and later for quarterly earnings (Joy et al. 1977). Drifts after quarterly earnings receive more attention because their magnitudes are markedly larger. Researchers have considered various explanations for apparent underreaction by investors to earnings news at announcements, followed by subsequent correction. The emerging consensus is that observed underreaction at announcement is the net effect of trades by two type of investors: noise traders and arbitrageurs. Mispricing originates because noise traders ignore positive autocorrelation, or persistence, in seasonally-differenced earnings. Arbitrageurs profit from this mispricing by trading in the direction of earnings news and move prices toward fundamental values. However, the incentives for arbitrageurs to trade decline as the gap between traded and efficient prices approaches the total costs of arbitrage. These costs include a variety of costs beyond direct trading costs, such as price impact and access to arbitrage capital (e.g., Lee and So, 2015; Ng et al. 2008). Subsequent correction occurs when noise traders receive signals about the predictable portion of next quarter's earnings that reflect underlying persistence.

Variation in drifts is shown to be related to proxies for both effects mentioned above. Drifts vary with three proxies for earnings persistence that explain original mispricing, before arbitrageurs intervene: earnings volatility (EVOL), an indicator variable for the fourth quarter (FQ4), and an indicator variable for negative earnings (LOSS). Persistence is expected to be lower for high EVOL (Cao and Narayanamoorthy, 2012), for fourth fiscal quarters (Rangan and Sloan 1998), and for firms reporting losses (Narayanamoorthy 2006). Drifts also vary with liquidity measures that proxy for limits to arbitrage (e.g., Bhushan 1994; Ng et al., 2008; Chordia et al., 2009): they decline as transaction costs fall and arbitrage activity increases (Ke and Ramalingagowda, 2005). Relatedly, Johnson and Schwartz (2000), Richardson et al. (2010), and Chordia et al. (2014) find that mispricing related to drifts has declined in recent years, especially among liquid stocks. In fact, there are indications that arbitrage activity has become so aggressive that prices overshoot efficient levels in some cases (Milian 2015).

Separate from arbitrageurs trading on public signals against noise traders who underestimate underlying earnings persistence, Vega (2006) introduces a role for privately informed trades prior to earnings announcements. More informed trading accelerates the incorporation of earnings information into pre-announcement stock prices, resulting in lower price movements at earnings announcements as well as less drift after earnings are announced.

2.3. Related research on off-exchange trading

2.3.1. Segmentation of uninformed order flow on dark venues

The trading mechanisms and regulatory oversight of dark venues discussed above cause uninformed (informed) trades to shift toward dark (lit) venues. The reasons for this increased concentration of informed trades on lit exchanges vary between institutional and retail orders. The vast majority of institutional orders are processed using computerized algorithms trading off immediacy of execution against execution costs. Dark pools, such as crossing networks, are more attractive for patient and uninformed liquidity trades that value price improvement over immediacy. In contrast, informed trades value immediacy. Moreover, they tend to crowd on the same, heavy side of the market, resulting in higher execution risk in dark pools, unlike uninformed trades that are distributed more evenly. Consequently, exchanges are more attractive for informed trades (e.g. e.g. Zhu 2014; Menkveld et al., 2017).

Retail trades, especially the majority that are uninformed, are filled via broker/dealer internalization (fourth dark venue above) because of "cream skimming" (e.g., Chordia and Subrahmanyam 1995 and Easley, Keifer, and O'Hara 1996). Almost all retail marketable (i.e. market or marketable limit) orders are routed by retail brokerages directly to OTC wholesale dealers.[10] Upon receipt of order flow, the wholesale market maker typically fills orders internally against its own account or—if an order is likely informed—routes it for execution to other wholesalers, other internalization pools, other market centers, or exchanges. Knowledge of customer identity allows market makers to separate informed from uninformed orders, to profit on retail orders that are on the "wrong" side of the market (i.e., against the direction of expected market movements in the short-term), and route remaining orders to other market centers.. Consequently, order flow eventually reaching exchanges is filtered: there are fewer opportunities for displayed liquidity providers—those posting limit orders on exchanges—to trade against retail order flow.

Existing empirical evidence is consistent with off-exchange trades containing less information than on-exchange trades. Jiang et al. (2012) and Hatheway et al. (2017) show that off-exchange trades have lower bid-ask spread, lower price impact, and lower information ratio—defined as information share (Hasbrouck, 1995) divided by volume share—than on-exchange trades. Comerton-Forde and Putnins (2015) reach a similar conclusion on the informativeness of off-exchange trades using an Australian sample. Reed et al. (2018) show that short sellers, likely to be informed, trade more on exchanges than in dark pools. To be sure, not all informed trades are expected to migrate to exchanges (e.g., Nimalendran and Ray 2014).[11]

Accounting research has also probed how informed and uninformed trades select between

[10] Many wholesalers have standing payment-for-order flow agreements with retail brokerages, typically paying 0.1 cent per share or less (SEC 2010).

[11] In particular, Ye and Zhu (2018) show both theoretically and empirically that informed traders with unique private information—such as hedge fund activists—trade more aggressively in dark pools than on exchanges.

lit and dark venues. The main focus is on how this choice varies around financial disclosures (earnings announcements and analyst recommendation revisions). Gkougkousi and Landsman (2018) and Balakrishnan and Taori (2017) find that dark volume increases temporarily on average around both types of events. They document that this bump in dark volume varies cross-sectionally with proxies for information asymmetry and quality of information environment. OFFEXCH is a dependent variable in these studies, and the question is whether and why it shifts temporarily around earnings announcements. For us, OFFEXCH is an explanatory variable, and we study whether and why it affects the level of PEAD.

2.3.2. Impact of segmenting trades between lit and dark venues on price discovery and PEAD

Theory suggests that accumulation of relatively more informed (uninformed) trades on lit exchanges (dark venues) should increase price discovery ahead of public announcement but reduce market liquidity (e.g., Hendershott and Mendelson, 2000; Zhu, 2014).[12] The former effect arises because OFFEXCH increases the signal-to-noise ratio in stock price (i.e. on-exchange proportion of informed to uninformed trades).[13] The latter effect is a consequence of the associated increase in adverse selection risk for liquidity suppliers on exchanges. Liquidity suppliers raise bid-ask spreads and reduce quote depth to recoup anticipated losses from providing liquidity to informed trades (e.g. Chakravarty and Sarkar, 2002; Dutta and Madhavan, 1997; Easley et al. 1996; Kluger and Wyatt, 2002). Wider spreads and lower depth increase transactions costs for both on and off-exchange trades.

The evidence based on U.S. data is generally consistent with OFFEXCH improving price

[12] The trade-off between price discovery (i.e. price incorporating private information) and liquidity is central to most microstructure theories (Foucault et al. 2013).

[13] In Zhu (2014), the signal-to-noise ratio increases with OFFEXCH as a result of three types of trader activity: (1) informed traders' acquisition of private information, (2) informed traders' venue choice, and (3) liquidity traders' venue choice.

discovery. The most direct evidence is provided in Brogaard and Pan (2018). They show that ATS trading, a subset of OFFEXCH, increases the ability of stock returns to predict upcoming earnings surprise, suggesting that more earnings information is incorporated into stock price before public announcement. Evidence in the finance literature that intraday price inefficiency—the degree to which stock prices deviate from random walks—declines with OFFEXCH is also consistent with improved price discovery (e.g. O'Hara and Ye 2011; Farley et al. 2018).

In contrast, evidence based on U.S. data about OFFEXCH harming liquidity is mixed.[14] O'Hara and Ye (2011) examine the first six months of 2008 and conclude that OFFEXCH reduces, rather than increases, effective bid-ask spreads. Hatheway et al. (2017) examine 120 stocks for one year—2011—and conclude that OFFEXCH increases spreads. Recent, concurrent studies that use the SEC Tick Size Pilot to investigate the causal effect of OFFEXCH on liquidity also reach different conclusions. Farley et al. (2018) and Rindi and Werner (2019) examine a short window (i.e. four to eight weeks) before and after the implementation of the program and find an insignificant change in effective bid-ask spread. SEC (2018, page 22), which examines a longer sample period (April 2016 to December 2017) reaches the same conclusion. In contrast, Chung et al. (2019) show that the "trade-at" rule, which significantly reduces OFFEXCH, results in a significantly smaller effective spread over the two-year window (i.e. October 2015 to October 2017) around the implementation of the program.

The mixed evidence is surprising given that theory strongly predicts a negative impact on liquidity. Perhaps the different results are due to small samples and the use of narrow windows

[14] Evidence is also mixed for non-US markets, albeit with different institutional features. For example, Foley and Putniņš (2016) investigate the introduction of minimum price improvement rules for dark trading in Canada in October 2012 and conclude that dark limit order markets reduce effective spread. However, Comerton-Forde et al. (2018) re-examine the same setting and reach a very different conclusion. They show that this rule eliminated intermediation of retail orders in dark venues and shifted retail orders toward lit markets with the lowest trading fee. They conclude that reducing retail order segmentation enhances lit liquidity.

around the implementation of the Pilot program. We re-examine the impact of OFFEXCH on liquidity using all U.S. firms with available data and consider a four-year window around implementation of the program. Our results leave no doubt: consistent with theory, OFFEXCH harms liquidity.

In sum, both theory and evidence suggest that OFFEXCH increases price discovery but harms liquidity. The former (latter) relation is the basis for the price discovery (liquidity) channel, which predicts a negative (positive) relation between OFFEXCH and PEAD.

3. Sample and descriptive results

3.1. Sample selection

While off-exchange trading has existed for a few decades, data availability has hampered meaningful large-sample analyses. Prior to 2007, all off-exchange trades were reported to exchanges but combined with on-exchange trades when recorded on the consolidated tape.[15] After March 5, 2007, Rule 601(b) of Regulation NMS under the Exchange Act requires OTC trades, including trades executed by ATSs, to be reported to the consolidated trade streams through one of the trade reporting facilities ("TRFs") operated by FINRA on behalf of exchanges, or through FINRA's ADF.[16] However, TRF reports before November, 2008 include trades on two large ECNs—BATS and DirectEdge—that should be viewed as similar to lit exchanges. Our sample begins in 2009 after which dark trading is identified relatively cleanly. Note that the identity of the particular dark pool or broker-dealer that executes the trade remains undisclosed.

As described in Table 1, Panel A our main sample begins with Compustat/CRSP firm-

[15] As a result, earlier studies of off-exchange trading such as broker/dealer internalization are limited to specific settings or proprietary data ,and often reach conflicting conclusions (e.g. Battalio 1997; Battalio, Greene, and Jennings 1998; Chung, Chuwonganant, and McCormick 2004).

[16] Securities Exchange Act Release No. 54084 (June 30, 2006), 71 FR 38935 (July 10, 2006) (File No. SR-NASD-2005-087) establishes rules for the reporting of off-exchange transactions through the new TRFs.

quarters with earnings announcement dates that are within three months of quarter-end and at least 30 trading days after the prior announcement. We follow recent research and measure earnings surprise (SUR) using both stock and earnings-based measures. The stock-based measure (EARET) is the firm's two-day earnings announcement window size-adjusted returns (e.g. Milian 2015) and the earnings-based measure (FE) is analyst forecast error (e.g. Livnat and Mendenhall 2006).[17] (The Appendix provides details for all variables.)

We exclude financial firms and observations with share price at fiscal quarter-end below $1, and require non-missing values for: (a) OFFEXCH and the two SUR measures; (b) two key measures of arbitrage risk that have been shown to explain cross-sectional variation in mispricing: idiosyncratic return volatility (IDVOL) and intraday mid-quote return variance (VAR); and (c) the three factors that proxy for persistence of earnings news: earnings volatility (EVOL), and indicator variables for fiscal fourth quarters (FQ4) and negative GAAP earnings (LOSS). We do not measure OFFEXCH during the earnings announcement window because Balakrishnan and Taori (2017) and Gkougkousi and Landsman (2018) show that the change in OFFEXCH at earnings announcement is related to earnings news. This could induce a mechanical relation with PEAD, one that is not anticipated by existing microstructure theories. (See Section 4.5 for related analyses.) Our final panel includes 82,502 firm-quarters from 2009Q1 to 2018Q2.

Following prior studies on off-exchange trades (e.g. Hatheway et al. 2017), we collect trades during regular trading hours (9:30 AM to 4:00 PM) and require positive values for trade price and shares traded.[18] For each trade, Daily TAQ (DTAQ) data separates trades executed on

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[17] We drop seasonally-differenced quarterly EPS (SUE) as an earnings-based measure of SUR. PEAD studies have over time replaced SUE with FE, because it better predict PEAD (e.g., Livnat and Mendenhall 2006).

[18] About 10 percent of overall trading occurs after hours, mostly on dark venues. We exclude those trades because some of the dark venue trades would have been sent to lit venues if they had not been closed.

stock exchanges (TAQ EX ≠ 'D') from those executed off exchanges (TAQ EX = 'D').[19] We estimate OFFEXCH over the pre-announcement period that begins on day +2 of quarter q-1 and ends on day −1 of quarter q. Figure 1, which shows the cross-sectional average OFFEXCH for fiscal quarters that end in different calendar quarters, indicates an upward trend: mean OFFEXCH increases from about 25 percent in 2009 to 34 percent in 2018.

To supplement our analyses based on the main sample, we leverage the natural experiment created by the SEC that offers the opportunity to compare a treatment group which experiences an exogenous decline in OFFEXCH with an otherwise similar control group that experiences an increase. Briefly, the SEC's Tick Size Pilot Program is a data-driven experiment designed to study the impact on trading and liquidity of widening minimum increments (tick sizes)—for both quotes and trades—for small capitalization stocks.[20] Prior to this intervention, implemented in October, 2016, the tick size for both quotes and trades is 1¢ After the intervention, four groups of randomly selected securities face different combinations of minimum quote and trade tick sizes, each set at either 1¢ or 5¢. Specifically, stocks in the control group continue to be quoted and traded at 1-cent increments. Stocks in test group G1 are quoted in 5-cent increments (i.e. quote rule), but market makers can execute trades at 1-cent increments. Stocks in test group G2 are both quoted and traded in 5-cent increments (i.e. trade rule), although some mid-quote trades are also allowed. Stocks in test group G3 have the same quote and trade rules as test group G2, but are additionally subject to a "trade at" prohibition: non-displayed orders cannot be executed within or at quoted bid/ask prices. In essence, non-displayed orders can only be executed *outside* quoted bid/ask prices.[21]

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[19] We exclude intermarket sweep order (ISO) trades when counting off-exchange trades, as these orders are most likely executed in non-exchange electronic communication networks (ECN) such as LavaFlow instead of dark pools or broker/dealer internalization.

[20] Details of the Tick Size Pilot Program are available at http://www.finra.org/industry/tick-size-pilot-program.

[21] Exemptions to trade-at rules are allowed for midpoint executions, retail investor executions with a minimum price improvement of $0.005, and negotiated trades.

Test group G3, which is subject to the quote, trade, and trade-at rules, is our treatment group, whereas test group G2 that is subject to just quote and trade rules is our control group. OFFEXCH should decline for the treatment group relative to the control group, because most trades on dark venues must now be traded outside the quoted spread. While we view a comparison of our treatment and control groups as reflecting the impact of a plausibly exogenous shock to OFFEXCH, we recognize that affected firms and investors might respond to the treatment in ways that also affect liquidity as well as PEAD. As a result, even though we ascribe any observed differences in these response variables to changes in OFFEXCH levels, we cannot rule out the possibility that they are due partially to other responses taken by firms and investors. We assume that these other responses have a smaller, second-order impact on PEAD, relative to the direct impact from the change in OFFEXCH due to the trade-at prohibition.

The results in Figure 2 describe daily levels of OFFEXCH for the treatment and control groups for two-year windows on either side of the October, 2016 implementation date of the pilot program.[22] OFFEXCH for the control group increases from about 35 percent to about 40 percent. Increasing the minimum quoted bid/ask spread for the control group drives more trades to dark venues to benefit from increased opportunities for price improvement, achieved by executing trades within the larger spread in dark pools. In contrast, OFFEXCH declines sharply for the treatment group to about 25 percent. Consistent with predictions, order flow shifts to exchanges when non-displayed orders are required to be executed outside quoted spreads. A difference-in-difference design that compares the treatment and control groups over the two-year windows before and after the change allows us to infer the impact of OFFEXCH on liquidity and PEAD.

[22] The sharp, periodic declines for OFFEXCH noted in Figure 2—which coincide with the third Fridays of March, June, September, and December, when contracts for futures/options for stocks and stock indexes expire—are due to sharp increases in on-exchange trading. Off-exchange trading remains unchanged.

We follow Rindi and Werner (2019) and Chung et al. (2019) to construct the Tick Size Pilot sample (see Panel B of Table 1). After requiring data necessary to calculate intraday liquidity measures, 317 control firms and 333 treatment firms remain. Quarterly data obtained for 3,636 (3,370) firm-quarters for the control (treatment) group are available for our PEAD analyses.

3.2. Descriptive statistics

The results reported in Table 2, Panel A provide statistics for the distributions of key variables. PEAD, the delayed price response per unit of earnings news, is missing as it is not estimated at the firm-quarter level. Instead, it is captured by the coefficient on earnings news in regressions predicting future size-adjusted returns ($SARET_{q+1}$). Returns are cumulated from the day after the current earnings announcement window (day +2 for quarter q) to the end of the earnings announcement window for the next quarter (day +1 for quarter q+1). Day 0 is the earlier of the announcement dates recorded in Compustat and IBES. We subtract returns earned over the same window by firms in the same market capitalization decile to obtain size-adjusted returns.[23]

The two earnings surprise measures are computed as follows. EARET is the size-adjusted return over the 2-day earnings announcement window that includes days 0 and +1 for quarter q. Size adjustment for returns is more important for EARET than for $SARET_{q+1}$ because announcement window returns are on average positive (e.g., Cohen et al. 2007) and vary with firm size (market capitalization). FE is actual earnings per share (EPS) minus the most recent consensus of analyst forecasts, both based on IBES data, scaled by price at prior quarter-end.

Table 2, Panel B provides pair-wise correlations among key variables, with Pearson (Spearman) correlations reported above (below) the main diagonal.[24] In general, the correlations

[23] Market capitalization deciles are computed as of the most recent calendar year-end before the earnings announcement.

[24] We omit NTRADES and TRSIZE to allow the correlation matrix to fit on one page.

are significant and consistent between Pearson and Spearman correlations. The relations are also generally consistent with those documented in prior research. The positive correlations between $SARET_{q+1}$ and the two earnings news measures—FE and EARET—confirm underreaction to earnings news in our main sample. Consistent with OFFEXCH being negatively related to liquidity, OFFEXCH is strongly positively related to effective spread (ESPD) and negatively related to depth (DEP).

4. Results

4.1. Relation between OFFEXCH and liquidity

We begin by investigating the impact of OFFEXCH on liquidity, as prior evidence is mixed. We first estimate panel regressions for two liquidity measures—ESPD and DEP—on OFEXCH, for our main sample. We add control variables used in prior studies (e.g. O'Hara and Ye 2011; Hatheway et al. 2017), including number of daily trades (NTRADES), average trade size (TRSIZE), intraday return volatility (VAR), share price (PRC), firm size (SIZE), and firm and quarter fixed effects. All independent variables are ranked into deciles by calendar quarter, and assigned values between –0.5 (lowest decile) and 0.5 (highest decile). The coefficients can thus be interpreted as the change in value of the dependent variable when the independent variable increases from the lowest to the highest decile.

Table 3, Panel A presents our results. The first column in Panel A shows that OFFEXCH is significantly positively associated with ESPD. As OFFEXCH increases from the bottom to the top decile, effective spread increases by 17.8% (= $e^{0.164} - 1$). The second column in Panel A shows that OFFEXCH is significantly negatively associated with DEP. As OFFEXCH increases from the bottom to the top decile, dollar depth at NBBO decreases by 17.6% (= $1 - e^{-0.193}$).

We turn to the Tick Size Pilot experiment to establish a causal relation, as the Panel A results could be due to OFFEXCH and liquidity being jointly determined. Comparing liquidity before and after the intervention for the treatment and control groups describes the impact of an exogenous decline in OFFEXCH. We consider just the TREAT*POST interaction for the difference-in-difference regressions, as we include firm and day fixed effects. The first column in Panel B of Table 3 confirms the results in Figure 2: OFFEXCH for the treatment group is substantially lower (about 13 percent) than that for the control group in the post period. The remaining columns in Panel B confirm that the lower levels of OFFEXCH for the treatment group result in higher market liquidity, evidenced by smaller spreads (ESPD) and greater depth (DEP), due to a decline in adverse selection risk when uninformed trades return to exchanges. Overall, the results in Table 3 support the theoretical prediction that OFFEXCH harms liquidity.

4.2. Relation between OFFEXCH and PEAD in the main sample

We turn next to the main question of interest: does the positive (negative) relation between OFFEXCH and price discovery (liquidity) result in a negative (positive) relation with PEAD? We first confirm that drift remains strong in our main sample by estimating regressions of $SARET_{q+1}$ on earnings news (EARET and FE). We then examine whether that drift is positively or negatively related to OFFEXCH by interacting earnings news with OFFEXCH, to determine which channel is more important.

Figure 3 offers preliminary findings. We report mean values of $SARET_{q+1}$ for the highest (Q5) and lowest (Q1) quintiles of earnings news, as well as hedge returns (Q5 – Q1), or the difference between the returns for the highest and lowest quintiles. Means for these three measures of future returns are reported separately for each quintile of OFFEXCH. Panels A and B refer to earnings news measured as EARET and FE, respectively. We find that future returns after good news (Q5) generally increase with OFFEXCH and that future returns after bad news (Q1) generally decrease with OFFEXCH. However, that increase is nonlinear. In Panel A, hedge returns are close to zero for the first three quintiles of OFFEXCH and increase to about 8 percent for the top OFFEXCH quintile. In Panel B, hedge returns are again close to zero for the first three quintiles of OFFEXCH and increase to about 5 percent for the top OFFEXCH quintile.

Observing a strong positive correlation between OFFEXCH and underreaction suggests that the negative liquidity impact of OFFEXCH is more important than improved price discovery. Figure 3 also indicates that the impact of OFFEXCH on PEAD is generally symmetric between the long and short sides. Observing substantial positive returns for the long side reduces the likelihood that our results are driven solely by arbitrageurs facing short sale constraints.

Table 4 provides regression results, where Panels A and B refer to earnings news measured as EARET and FE, respectively. Again, all independent variables are sorted into deciles each calendar quarter and assigned values between -0.5 and 0.5. The coefficients can therefore be interpreted as the hedge return over the next quarter from going long (short) in the highest (lowest) decile of that variable. Note that the coefficients, *t*-statistics, and adjusted R^2 reported in Table 4 regressions are based on pooled regressions with standard errors clustered by firms and by quarters (Gow et al. 2010).[25] All regressions include controls for four factors that have been shown to predict returns: beta risk (BETA), market capitalization (SIZE), book-to-market ratio (BTM), and momentum based on returns over the prior 11 months (MOM11).

The coefficient of 0.026 on EARET in Column (1) in Panel A suggests that a long/short position in extreme deciles of earnings news generates a hedge return of 2.6 percent, after controlling for BETA, SIZE, BTM, and MOM11. Introducing the interaction between EARET and OFFEXCH in column (2) provides results similar to those in Figure 3: The interaction coefficient suggests that the difference between the hedge returns for the top and bottom OFFEXCH deciles

[25] Results are similar (available upon request) when we use the Fama and Macbeth (1973) methodology.

is 10.0 percent. The larger hedge return in Table 4, relative to Figure 3, is likely due to earnings news deciles capturing more underreaction than quintiles. The insignificant coefficient on the main effect of OFFEXCH indicates that off-exchange trading levels don't predict future returns.

Figure 4, Panel A describes time-series variation in two coefficients from Table 4, Panel A: EARET in column (1) and EARET*OFFEXCH in column (2). While there is variation across quarters for both coefficient estimates, the plots suggest two takeaways. First, PEAD continues to exist in our more recent sample because the coefficient on EARET is positive in all but two quarters. Second, and more relevant to this study, the interaction between EARET and OFFEXCH is always positive. That is, in every quarter, firms with higher levels of off-exchange trading are associated with more drift than firms with less off-exchange trading.

Column (3) in Table 4, Panel A includes the three variables that have been shown in prior research to explain cross-sectional variation in the autocorrelation in seasonally-differenced quarterly earnings that noise traders underreact to: an indicator variable for the presence of a loss (LOSS), an indicator variable for the fiscal fourth quarter (FQ4), and earnings volatility (EVOL). The significant negative interaction for FQ4 is consistent with the results in Rangan and Sloan (1998): drifts are lower after earnings announcements for the fourth quarter. The positive coefficients for the interaction terms with EVOL is inconsistent with the negative interaction observed in Cao and Narayanamoorthy (2012), and negative yet insignificant coefficients for the interaction terms with LOSS differ from the negative, significant coefficient in Narayanamoorthy (2006). We note, however, that those two prior studies are based on earnings news measured as forecast error, not EARET. As in column (2), none of the main effects are significant.

The corresponding results in Panel B of Table 4 and Figure 4 suggest similar inferences when earnings news is measured as forecast error. For brevity, we do not report coefficient estimates for controls and main effects. The coefficient on FE in column (1) is positive and significant confirming that PEAD exists in our sample period. The coefficient on FE*OFFEXCH in column (2) is positive and significant, indicating that PEAD increases with OFFEXCH. Variation over time in these two coefficients shown in Panel B of Figure 4 provides inferences similar to those in Panel A. And the coefficient FE*OFFEXCH remains positive and significant in column (3) when we include controls for the three factors that proxy for persistence in earnings news. One difference is that the coefficient on FE*EVOL is negative and significant, not positive as in Panel A, consistent with the results in Cao and Narayanamoorthy (2012).

4.3. Can liquidity measures explain variation in the relation between OFFEXCH and PEAD?

If the positive relation observed between OFFEXCH and PEAD is due to the negative impact of OFFEXCH on liquidity, we expect this relation to become insignificant when we include controls for liquidity. Directly capturing the impact of liquidity, which reflects the higher arbitrage costs that result in residual underreaction to earnings news, on PEAD should eliminate any role for OFFEXCH. Columns (4) through (6) in both Panels of Table 4 describe the impact of sequentially introducing three measures of liquidity: Effective spread (ESPD); Depth (DEP); and idiosyncratic volatility in daily returns over the prior year (IDVOL).[26] We interact each liquidity measure with earnings news to control for its effect on PEAD, and also allow for a main effect to control for any relation between those measures and the level of future returns.

The main conclusion from this analysis is that while the relation between OFFEXCH and PEAD declines when liquidity controls are introduced, it remains substantial and highly significant. The coefficient on EARET*OFFEXCH in Panel A declines from over 9 percent to just above 6 percent, and the coefficient on FE*OFFEXCH in Panel B declines from over 7 percent to

[26] Untabulated results show that the results remain relatively unchanged when we add a fourth measure of liquidity to column (6): intraday mid-quote variance computed at one-minute intervals (VAR).

around 4 percent. The liquidity measure that exhibits the most significant relation with PEAD is ESPD, as its interaction with earnings news remains significant in all specifications. Interactions with the remaining liquidity measures are generally statistically insignificant, but that lack of incremental significance may be due to multicollinearity, induced by the high correlations among the liquidity measures, noted in Table 2, Panel B.

Failing to eliminate the positive relation between OFFEXCH and PEAD suggests two non-mutually exclusive possibilities. First, the specific controls we introduce, which reflect liquidity faced by average, small traders (e.g. Jones and Lipson 2001), measure with considerable error the liquidity that is relevant for arbitrageurs. Second, many other factors, beyond the costs created by lower liquidity, are relevant for arbitrageurs. A fuller consideration of the various factors that affect arbitrage activity includes the costs of financing, hedging, and model error (e.g., Lee and So 2015). Regardless, observing that OFFEXCH plays an economically and statistically significant role in explaining PEAD suggests that mispricing research should consider levels of off-exchange trading as a proxy for hard-to-measure arbitrage costs.

4.4. Results from the natural experiment created by the SEC's pilot project

Our next analysis returns to the natural experiment to investigate causality in the positive relation between OFFEXCH and PEAD observed for the main sample.[27] The results reported in Panel A of Table 5 investigate whether PEAD is indeed present in this limited sample, representing 650 small capitalization firms during the sixteen quarters surrounding October, 2016. We estimate a regression of returns over the next quarter ($SARET_{q+1}$) on our two earnings news measures (SUR), in the presence of controls for the four variables that explain levels of returns: BETA,

[27] We are less concerned about reverse causality, from PEAD to OFFEXCH, as OFFEXCH is measured before the PEAD holding period. It seems unlikely that traders choose dark versus lit venues in anticipation of underreaction to earnings news.

SIZE, BTM, and MOM11. Our results suggest that PEAD is observed when earnings news is measured as announcement returns (EARET) but not when it is measured as forecast error (FE).

The analysis reported in Panel B investigates whether PEAD declines for the treatment group, relative to the control group, after the intervention introduced by the pilot program. This difference is captured by the coefficient on SUR*TREAT*POST. We include firm and quarter fixed effects, interactions between earnings news and those fixed effects, as well as controls for the four factors that explain levels of returns.[28] The main result from this analysis is that PEAD declines significantly for the treatment group when earnings news is measured as EARET. This finding is consistent with the positive relation between PEAD and OFFEXCH observed for the main sample. The coefficient on SUR*TREAT*POST is not significant for FE. We suspect that this lack of significance arises because SUR is not significant for FE in Panel A. If PEAD is itself insignificant when earnings news is measured as forecast error, variation in PEAD due to variation in OFFEXCH will likely also be insignificant.

To probe causality, we conduct a placebo test and re-estimate the regressions in Panels A and B for the same treatment and control firms over a pseudo implementation date: June 30, 2014. We define 2012Q3 – 2014Q2 as the pre-treatment window and 2014Q3 – 2016Q2 as the post-treatment window for the placebo sample. The results in Panels C and D show that while significant PEAD is observed for both measures of SUR in the placebo sample (significant coefficient on SUR), that drift is similar across the treatment and control groups (insignificant coefficient on SUR*TREAT*POST). In addition to providing support for the inference that our Panel B results reflect the causal impact of OFFEXCH on PEAD, these results suggest that

[28] We do not include main effects for TREAT and POST because of included firm and quarter fixed effects. And we do not include the main effect for SUR and the interaction terms—TREAT*SUR and POST*SUR—because of included interactions between earnings news and firm or quarter fixed effects.

treatment and control firms are similar prior to the implementation of the Tick Size Pilot Program.

4.5. Relation between OFFEXCH at the earnings announcement and PEAD

In our main analysis reported in Table 4, we measure OFFEXCH during the pre-announcement window because the change in OFFEXCH at earnings announcements is related to earnings news. Our concern is that the level of OFFEXCH during earnings announcements may be related to corresponding changes in microstructure effects, which creates a mechanical relation with PEAD. Even though untabulated results suggest that the change in OFFEXCH at earnings announcement is small relative to pre-announcement levels, we confirm that incorporating this change in OFFEXCH does not affect our results. We add to the specification in column (6) of Panels A and B in Table 4 changes between the pre-announcement and announcement windows in levels of OFFEXCH ($\Delta OFFEXCH_{EA}$), as well as changes in ESPD ($\Delta ESPD_{EA}$) and DEP (ΔDEP_{EA}. The results in Table 6 confirm that the positive relation between OFFEXCH and PEAD remains similar to that reported in Table 4. Surprisingly, even though the level of DEP is insignificant in Table 4, change in DEP (ΔDEP_{EA}) are positively associated with PEAD, suggesting that drifts are larger when market depth increases more at earnings announcement.

5. Robustness checks

We conduct a number of additional analyses to investigate the robustness of our two main findings: (a) PEAD increases with OFFEXCH, and (b) this positive relation survives controls for a host of arbitrage cost measures. Given the volume of results obtained, we offer a summary discussion below and tabulate some key analyses in an Online Appendix.

5.1. Contemporaneous price response to earnings news.

One approach used in the prior literature to confirm underreaction (e.g., Ng et al., 2008) is to determine if the contemporaneous response to earnings news (earnings response coefficient or ERC) varies *negatively* with the magnitude of news. We note that the contemporaneous price response is not as reliable a measure of underreaction to earnings news as the delayed price response, because prior research has shown that ERC is determined by a host of factors, some of which are likely correlated with OFFEXCH. Such factors include leakage of earnings news prior to its public disclosure, earnings persistence, and risk. We therefore view these analyses as offering indirect evidence on the two main findings observed for delayed investor responses in Section 4.

For ERC regressions, we are limited to just one measure of earnings news (FE), as the other measure (EARET) is now the dependent variable. Table A1 in the online appendix describes variation in ERC across deciles of OFFEXCH using regression specifications similar to those in Panel B of Table 4. Results in column (1) of Table A1 confirm that ERC (the coefficient on FE) is clearly positive, even in the presence of controls for factors that explain variation in announcement returns (such as BETA and SIZE). More important, the coefficient on FE*OFFFEXCH is negative and significant in column (2), suggesting that ERC declines with OFFEXCH. This decline is consistent with the liquidity channel: investors underreact to FE and that underreaction increases with OFFEXCH.[29]

The remaining columns confirm that the negative relation between ERC and OFFEXCH survives controls for the three factors that explain variation in earnings persistence (column 3) as well as controls for the four liquidity measures that are related to arbitrage costs (columns 4 to 7). The coefficient on FE*OFFEXCH remains negative and significant, although the magnitude

[29] It is also consistent with the *basis* for the price discovery channel. Higher OFFEXCH results in prices reflecting more earnings news before the announcement window, leaving less opportunity for prices to reflect earnings news during the announcement window (Vega, 2006). However, the results in Section 4 suggest that high OFFEXCH is not associated with lower *future* returns, which is the implication of the price discovery channel that we study.

declines substantially. Overall, results in Table A1 are consistent with the inference from our Table 4 results: investor underreaction to earnings news increases with OFFEXCH.

5.2. Controls for other measures of arbitrage costs.

In our main analysis, we control for intraday high-frequency measures of liquidity: ESPD and DEP, which are conceptually better than low-frequency measures. It is possible, however, that low-frequency measures of liquidity better explain the relation between OFFEXCH and PEAD. We begin with the regression specification in column (6) of Panels A and B of Table 4 and include seven additional low-frequency liquidity measures that might reasonably capture arbitrage costs: The Amihud (2002) liquidity measure; level of institutional ownership; share price; intraday quoted spread; market capitalization; share turnover; and on-exchange share turnover. We include these measures one at a time as well as jointly. The results in Table A2 of the online Appendix suggest that while the inclusion of these variables increases the overall explanatory power (e.g. R^2 increases from 51% to 62% when earnings news is defined as EARET), the magnitude and significance of the coefficients on SUR*OFFEXCH in Panels A and B—corresponding to earnings news measured as EARET and FE, respectively—remain relatively unchanged.[30]

The measures of effective spread and depth considered in Table 4 are based on pooling all trades during the pre-announcement window and giving each trade the same weight. It is likely that the relevant costs faced by arbitrageurs reflect spread and depth associated with just on-exchange trades, and the weight given to measures associated with different trades varies depending on their relevance to specific arbitrage trading strategies. To investigate this possibility, we begin with the base case and switch to depth/spread for just on-exchange trades, and consider

[30] Untabulated results indicate that this finding persists when we replace all liquidity measures, high and low frequency, with their first two principal components, estimated both over the pooled sample as well as separately for each quarter (to avoid a look-ahead bias).

four alternative weighting schemes: equal weight; value weight based on on-exchange turnover; value weight based on off-exchange turnover; and value weight based on absolute value of return. The results reported in Panels A and B of Table A3 in the online Appendix indicate little change in the coefficients on SUR*OFFEXCH, relative to the base case. Overall, OFFEXCH remains a reasonable proxy for hard-to-measure arbitrage costs as it explains variation in PEAD beyond that explained by a host of other observable proxies for arbitrage costs.

5.3. Importance of retail internalization.

Our final robustness analysis considers the importance of retail internalization, one of the four venues associated with OFFEXCH. Our motivation to do so arises from untabulated analyses we conducted that examines variation in different cuts of the sample based on observable attributes of trades that allow insights about the specific source/factor that generates a positive relation between OFFEXCH and PEAD. Examples of cuts we consider include ATS (i.e. alternative trading system) versus non-ATS venues; block versus non-block trades; trades executed at the midpoint, within and outside quoted bid/ask prices; and trades executed at half-penny, sub-penny (fractions other than half), and round pennies. ATS venues comprise crossing networks and nondisplayed limit order books, whereas non-ATS venues comprise PING destinations and retail internalization.[31] Block trades are more likely to be uninformed trades that are executed in crossing networks at the midpoint of bid/ask prices, relative to non-block trades. Retail internalization is more likely to appear as sub-penny trades, whereas on-exchange trades at quoted ask/bid prices are more likely to be round penny trades.

We replace the SUR*OFFEXCH interaction in the base PEAD specification with interactions between SUR and the different subsamples created in each cut. For example, we

[31] ATS trading volume, beginning in May 2014, is available on a weekly basis from the FINRA OTC Transparency Data website (https://otctransparency.finra.org/TradingDetailFile).

replace SUR*OFFEXCH with SUR*ATS and SUR*non-ATS. We are unable to find consistent patterns across the different specifications that allow us to narrow the subset of off-exchange trades that drive the overall positive relation with PEAD. For example, block trades exhibit significant coefficients, and even larger magnitudes than non-block trades when earnings news is measured by EARET, and yet the interaction with midpoint trades is insignificant.

One coefficient estimate that is large and significant is the interaction with non-ATS. This raises the potential that it is variation in retail internalization—one of the two venues included in non-ATS—that is mainly responsible for the observed relation between OFFEXCH and PEAD. The significant results we observe in Table 5 for the Tick Size Pilot experiment suggest otherwise because retail trades are by design excluded from the restrictions imposed on the treatment group.[32] Regardless, we consider three possible ways in which retail trades might create the observed positive relation. They are based on the assumption that retail trades represent noise trades that create the originating underreaction to earnings news.[33]

First, firms with high levels of retail trades might exhibit lower pre-announcement anticipatory response to upcoming earnings news, which then surfaces as higher post-announcement price responses. We replace returns over the next quarter in the base specification with returns during the pre-announcement period and report results in columns (1) and (4) of Table A4 in the online Appendix. The coefficient on SUR*OFFEXCH, which should be negative under this alternative explanation, is positive for both measures of earnings news (and significant for FE). The significant coefficient on SUR*OFFEXCH in column (4) is also observed in Brogaard and Pan (2018).

[32] Untabulated results show that both ATS and non-ATS market shares decline significantly for the treatment group relative to the control group in the Tick Size Pilot experiment.

[33] We recognize that this assumption runs counter to the evidence in Boehmer et al. (2017), which suggests that retail trades—both on and off-exchanges—are on average informed and predict future returns.

Second, firms with high levels of retail trades might be associated with high buy/sell imbalances during earnings announcement windows, and those imbalances are contrary to the news announced. Stated differently, the observed underreaction associated with OFFEXCH that remains after controlling for liquidity measures is due to just the originating mispricing by noise traders (which are all retail traders under this alternative explanation) not arbitrage activity that is not fully captured by the included liquidity measures. We use the Boehmer et al. (2017) methodology to identify retail trades (based on the fraction of total trades that are sub-penny trades) and the Lee and Ready (1991) methodology to separate buys and sells. This allows a measure of abnormal retail net purchases during the announcement window, relative to levels in the pre-announcement window. Our results reported in columns (2) and (5) of Table A4 indicate coefficients on SUR*OFFEXCH that are similar in magnitude and significance to the base case, suggesting that abnormal net retail purchases do not affect the relation between OFFEXCH and PEAD. Surprisingly, we find significant positive coefficients on this retail buy/sell imbalance variable, suggesting that PEAD is in fact stronger when retail investors trade in the direction of earnings news.

Finally, firms with high levels of retail trades might be associated with a general level of mispricing that is not reflected specifically in buy/sell imbalance during the announcement window. We include an interaction between retail trading volume, based on the Boehmer et al. (2017) methodology, and earnings surprise. Again, the coefficient estimates on SUR*OFFEXCH remain similar in magnitude and significance to those in the base case.

6. Concluding thoughts

Off-exchange trading on dark venues—without pre-trade transparency—has increased substantially over the past 30 years, raising concerns among regulators and exchanges about its impact on price discovery. Microstructure research suggests that OFFEXCH increases segmentation: patient, uninformed, liquidity trades that value price improvement move to dark venues, while informed trades that value immediacy of execution gravitate toward exchanges. This segmentation increases the signal-to-noise ratio in stock prices, which improves price discovery. But segmentation also reduces liquidity because liquidity providers face higher adverse selection risk. We investigate how this trade-off between reduced liquidity and improved price discovery impacts post-earnings-announcement drift, a long-standing accounting anomaly that suggests investors underreact to public announcements of accounting earnings. Prior research suggests that liquidity and price discovery ahead of public announcement have opposite effects on drift.

Our investigation reveals a positive relation between OFFEXCH and PEAD. This result holds for a comprehensive panel of US firms as well as for a natural experiment created by the SEC's tick size pilot conducted on a sample of low capitalization firms. This positive relation is consistent with the liquidity channel being more important than the price discovery channel. Findings supporting the liquidity channel are consistent with drifts being due to limits to arbitrage, because arbitrage costs are likely to increase when liquidity declines. Arbitrageurs trade to correct underreaction to earnings news, but only up to the point when remaining profit opportunities fall below arbitrage costs.

The positive relation between OFFEXCH and underreaction remains significant, both statistically and economically, when we include controls for a host of proxies for liquidity. This incremental ability of OFFEXCH to explain mispricing suggests two possible interpretations that are consistent with the limits to arbitrage explanation. First, the liquidity cost proxies we consider do not reflect the transaction costs actually paid by arbitrageurs. Second, observed transactions costs do not represent all costs faced by arbitrageurs (Lee and So 2015)

Overall, we document that underreaction to earnings news increases with OFFEXCH. Recent increases in OFFEXCH should thus be a concern for regulators focused on dissemination of public disclosures. Our results support the view that observed underreaction reflects the net effect of noise traders underreacting to earnings news and arbitrageurs trading in the direction of earnings news, up to the limit of arbitrage costs (Ng et al. 2008). Our finding that OFFEXCH continues to explain a substantial fraction of variation in PEAD suggests that it can be used as a proxy for arbitrage costs by researchers studying the role of arbitrage in mispricing.

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Appendix: Variable definitions

The current quarter is labeled quarter q, and the prior (next) quarter is q-1 (q+1). The *earnings announcement window* includes day 0 and day +1. The *pre-announcement window*, for which we require a minimum of 30 trading days, begins on day +2 of quarter q-1's earnings announcement and ends on day −1 of quarter q's earnings announcement. The *post-announcement window* begins on day +2 of quarter q's announcement and ends on day +1 after quarter q+1's announcement.

Variable	**Definition**
Dependent variables	
$SARET_{q+1}$	Size-adjusted returns over the post-announcement window.
Main independent variables	
OFFEXCH	Off-exchange trading ratio over the pre-announcement window is defined as average daily ratio of shares traded off stock exchanges to total number of shares traded during regular hours (09:30 to 16:00) from the daily TAQ (DTAQ) database. Off-exchange trades are indicated by exchange code = 'D', indicating it was recorded on a trade reporting facility (TRF).
EARET	Size-adjusted returns over the earnings announcement window.
FE	Analyst forecast error is IBES actual EPS minus IBES latest consensus mean EPS forecast, scaled by share price at quarter q's fiscal quarter end.
Control variables explaining cross-sectional variation in drift	
EVOL	Natural logarithm of earnings volatility, which is defined as the standard deviation of quarterly ROA (net income/average total assets) over the past 8 quarters.
FQ4	Indicator variable = 1 if quarter q is a fiscal fourth quarter, = 0 otherwise.
LOSS	Indicator variable = 1 if GAAP EPS of quarter q is negative, = 0 otherwise.
DEP	Average daily market depth at NBBO over the pre-announcement window. Daily depth is defined as volume-weighted average dollar depth at NBBO computed over all trades, including both on-exchange and off-exchange trades, during regular trading hours in that day (see Holden et al. 2014 for details). Ln(DEP) is the natural logarithm of DEP.
ESPD	Average daily percentage effective spread over the pre-announcement window. Daily percentage effective spread is volume-weighted average percentage effective spread computed over all trades, including both on-exchange and off-exchange trades, during regular trading hours in that day. The percentage effective spread is twice the signed ('+' for buyer initiated and '-' for seller initiated) difference between log price of the trade and log midpoint between NBBO one nanosecond before the trade (see Holden et al. 2014 for details). For off-exchange trades, we adjust reported trade time as described in the variable definition for MIDPOINT. We use the Lee and Ready (1991) algorithm to determine whether a trade is buyer- or seller- initiated. Ln(ESPD) is the natural logarithm of ESPD.
IDVOL	Natural logarithm of idiosyncratic return volatility measured over the past year ending in quarter q. We require a minimum of 120 trading days.
VAR	Natural logarithm of average daily intraday mid-quote return variance over the pre-announcement window. Intraday mid-quote return is computed at 1-minute frequency.
Control variables explaining cross-sectional variation in returns	
BETA	Equity beta over the past year ending in quarter q, with a minimum requirement of 120 trading days.

BTM	Book-to-market ratio is defined as book value of common shareholders' equity at the beginning of quarter q divided by the market value at the end of quarter q.
MOM11	Compounded returns over the 11-month window ending in the 2^{nd} month of the current quarter. We require a minimum of 120 trading days.
SIZE	Natural logarithm of market value at the end of quarter q.
Control variables explaining cross-sectional variation in liquidity	
NTRADES	Average daily number of trades over the pre-announcement window.
TRSIZE	Average daily trade size over the pre-announcement window. Daily trade size is number of shares traded divided by number of trades.
PRC	Natural logarithm of share price at the end of quarter q.

Figure 1. Time-series of average levels of off exchange trading

This figure plots the quarter-by-quarter sample means for off-exchange trading ratio (OFFEXCH), measured over a pre-announcement window. The sample includes 82,502 firm-quarters from the first quarter of 2009 to the second quarter of 2018. OFFEXCH for a firm-quarter equals the average of daily percentages across trading days in that quarter. See Appendix for details of variables.

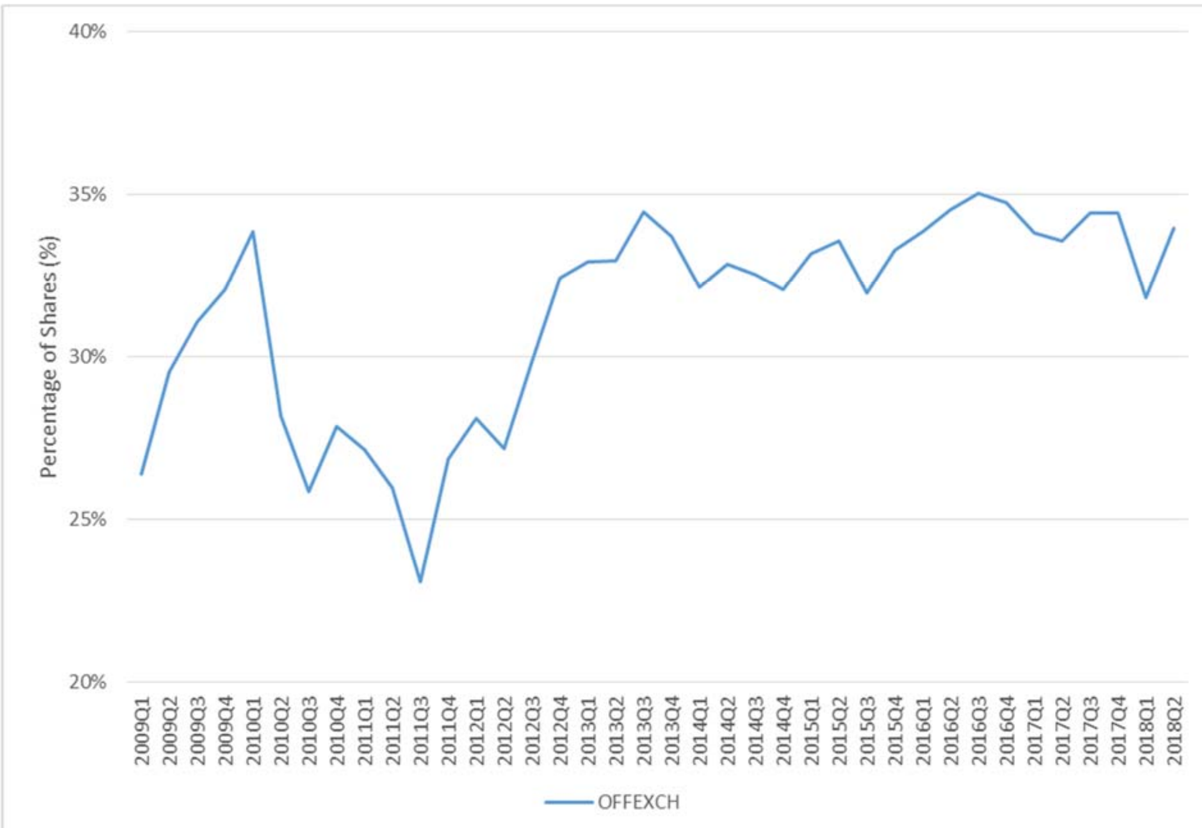


Figure 2: Impact of SEC Tick Size Pilot Program on off-exchange trading

This figure plots the daily portfolio mean of the percentage of shares traded off stock exchanges for our treatment group and control group in the SEC Tick Size Pilot sample. Daily off-exchange trading ratios are plotted for the four-year window around the staggered implementation of the pilot program during October 2016. The Tick Size Pilot program refers to our treatment and control groups as test group three (TEST G3) and test group two (TEST G2), respectively. Daily list of stocks included in the pilot program is available at http://www.finra.org/industry/tick-size-pilot-program.

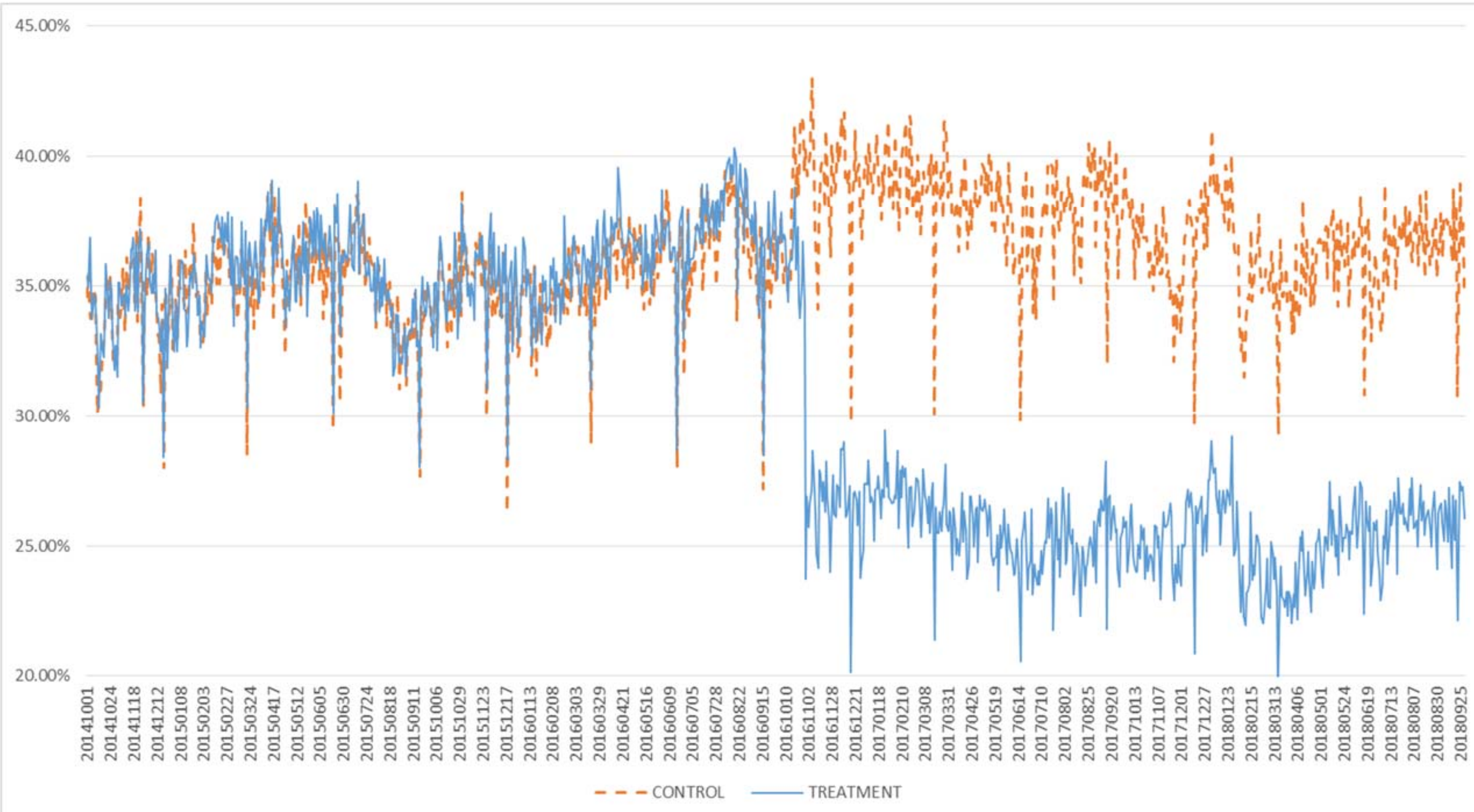
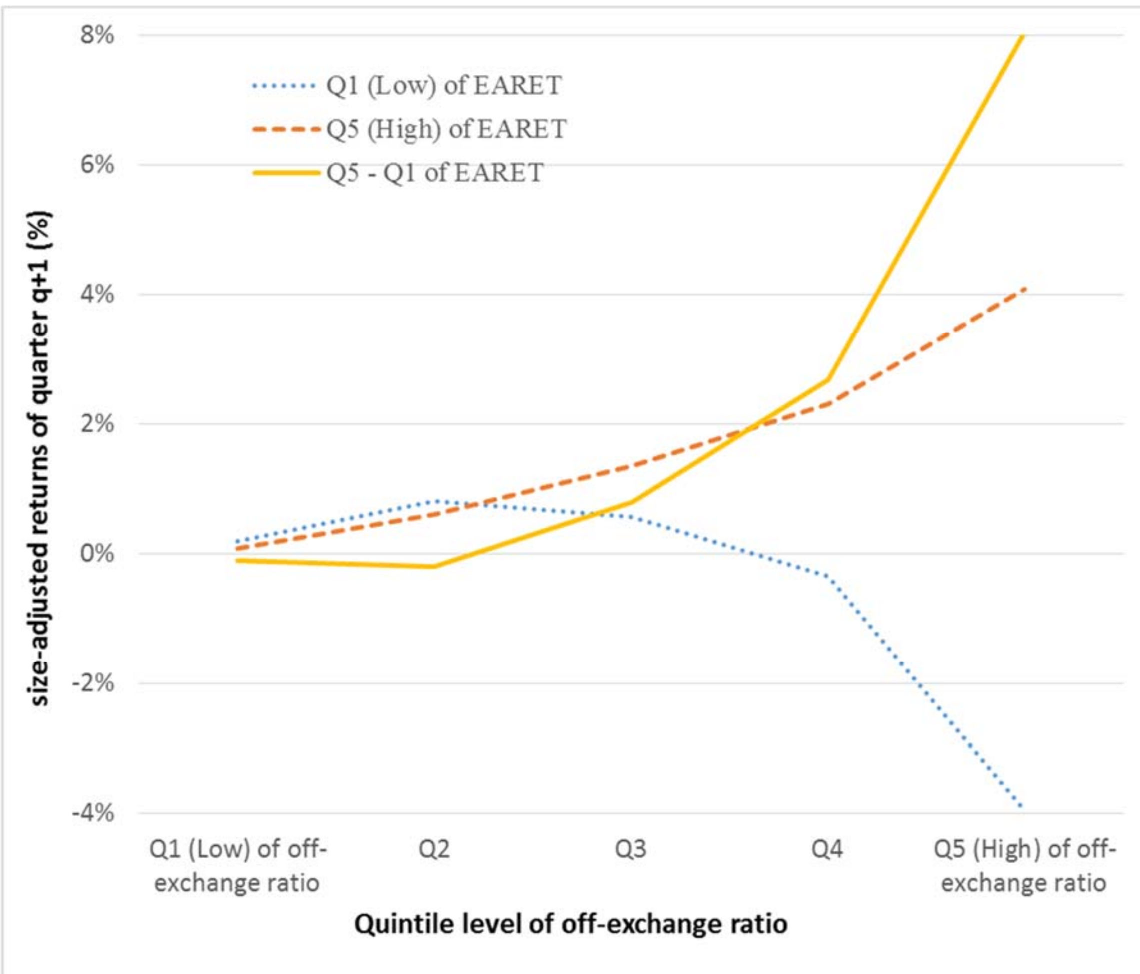


Figure 3: Relation between off-exchange trading and post-earnings-announcement-drift

We plot mean size-adjusted returns over the next quarter ($SARET_{q+1}$) for the lowest (Q1) and highest (Q5) quintile of earnings surprise, across quintiles of off-exchange trading ratio (OFFEXCH). Earnings surprise is measured as earnings announcement returns (EARET) in Panel A and analyst forecast error (FE) in Panel B. OFFEXCH for a firm-quarter is the average daily percentage of shares traded off stock exchanges to total number of traded shares, measured over a pre-announcement window. Portfolio "Q5 – Q1 of EARET" and "Q5 – Q1 of FE" represents returns to a hedge portfolio constructed by investing long/short in Q5/Q1 for the corresponding measures of earnings surprise. The sample is ranked independently into quintile portfolios of earnings surprise and off-exchange ratio for each calendar quarter. We report means of portfolio returns for each calendar quarter in our sample. The sample includes 82,502 firm-quarters from 2009Q1 to 2018Q2. See Appendix for details of variables.

Panel A. Earnings surprise is defined as earnings announcement return (EARET)



Panel B. Earnings surprise is defined as analyst forecast error (FE)

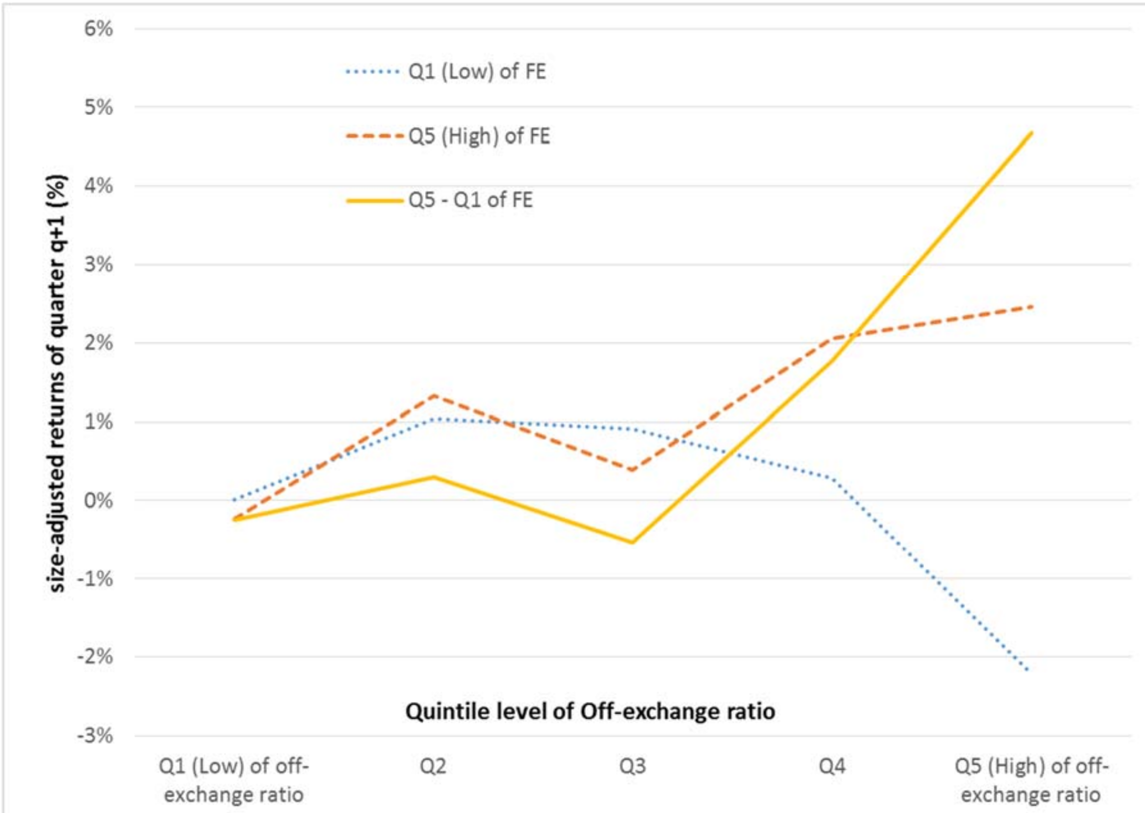
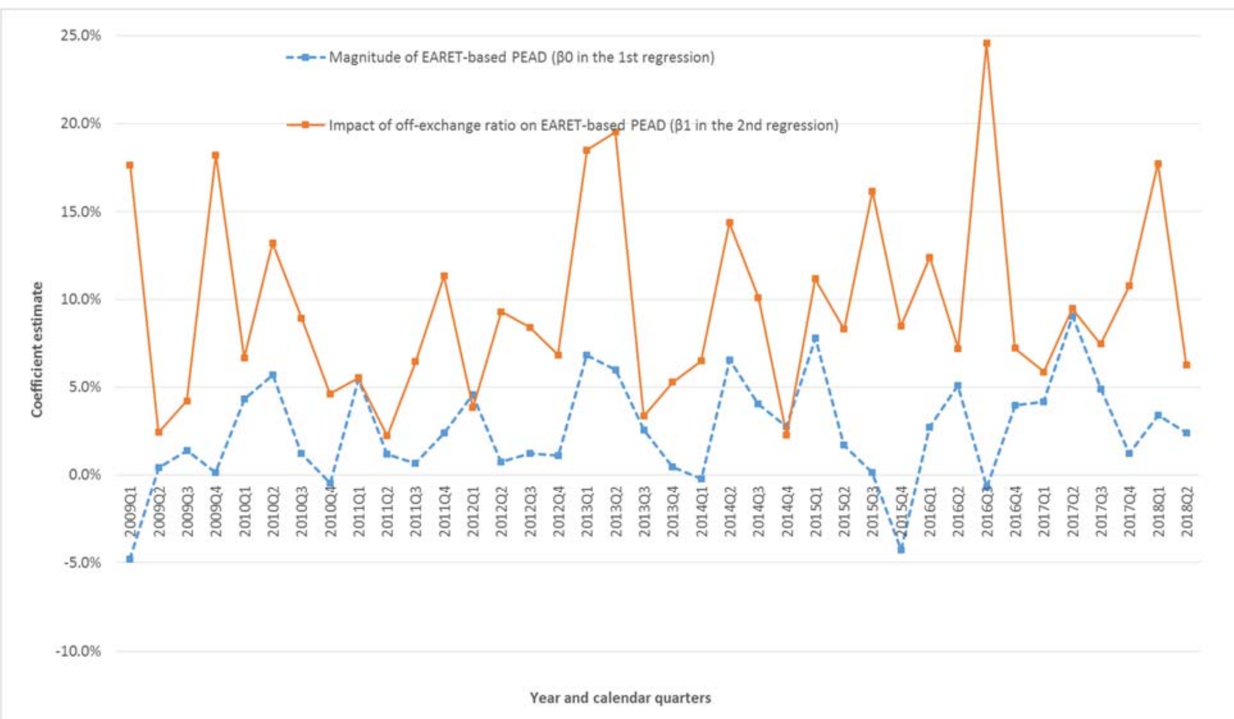


Figure 4: Variation over time in the relation between off-exchange trading and post-earnings-announcement-drift (PEAD)

The dashed (solid) line in these figures is the coefficient estimate β_0 on SUR (β_1 on SUR*OFFEXCH) from the first (second) cross-sectional regression below, estimated within calendar quarters:
$SARET_{q+1} = \alpha + \beta_0*SUR + Controls + \varepsilon.$
$SARET_{q+1} = \alpha + \beta_0*SUR + \beta_1*SUR*OFFEXCH + \beta_2*OFFEXCH + Controls + \varepsilon.$
$SARET_{q+1}$ is the size-adjusted return over the next quarter, SUR is earnings surprise defined as size-adjusted returns at current quarterly earnings announcement (EARET) in Panel A and analyst forecast error (FE) in Panel B. OFFEXCH is the average daily percentage of shares traded off stock exchanges measured over a pre-announcement window. Controls are BETA, SIZE, BTM, and MOM11.
All independent variables are ranked into deciles by calendar quarter and assigned values between -0.5 (lowest decile) and 0.5 (highest decile).
The coefficient β_0 in the first regression indicates the hedge portfolio return earned over the next quarter from investing long (short) in the highest (lowest) EARET or FE decile, unconditional on the level of OFFEXCH.
The coefficient β_0 in the second regression (not reported below) indicates the hedge portfolio returns earned over the next quarter from investing long (short) in the highest (lowest) EARET or FE decile, for the median level of OFFEXCH. The coefficient β_1 in the second regression indicates the change in that relation as OFFEXCH increases from the lowest to the highest decile.
The sample includes 82,502 firm-quarters from 2009Q1 to 2018Q2. See Appendix for details of variables.

Panel A. Earnings news is defined as earnings announcement return (EARET)



Panel B. Earnings news is defined as analyst forecast error (FE)

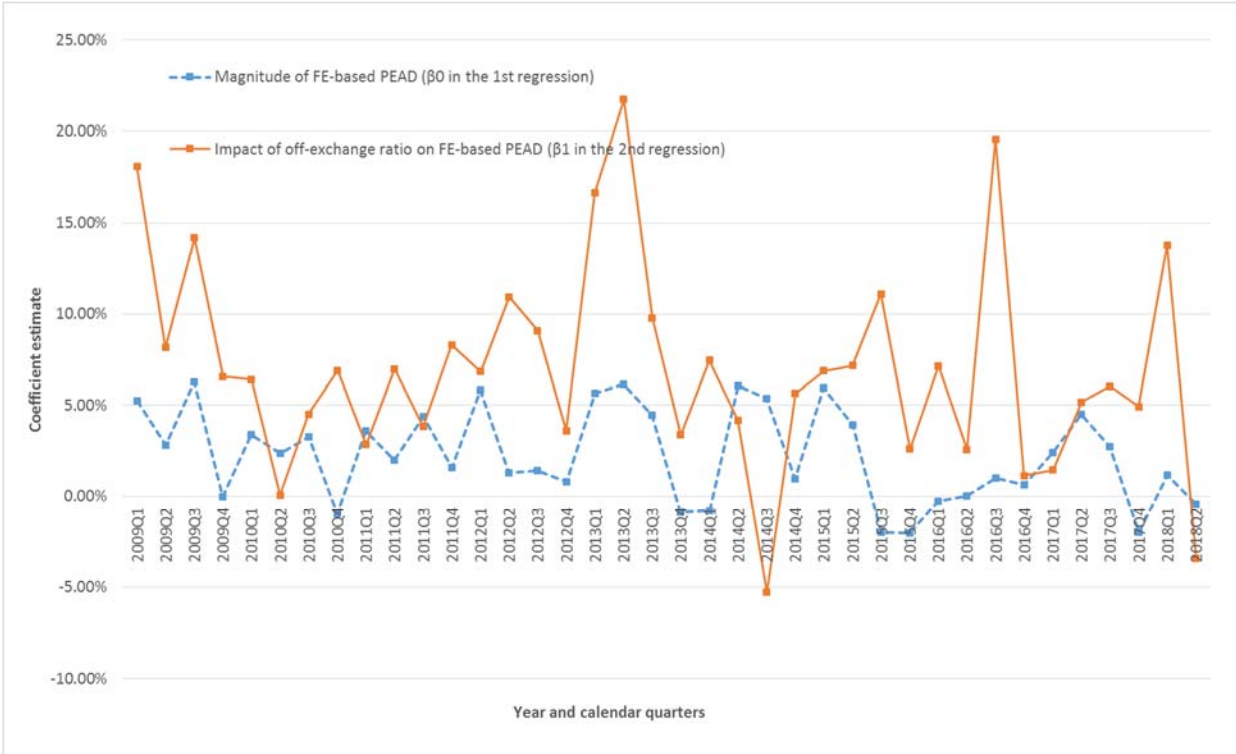


Table 1: Sample selection

Panel A: Data collection for the main sample (panel)	Firm-quarters remaining
Compustat/CRSP firm-quarters of common stocks from 2009Q1 to 2018Q2 satisfying the following requirements: 1. earnings announcement date is no more than 92 calendar days after fiscal quarter end; and 2. earnings announcement date is at least 30 trading days after previous quarterly earnings announcement.	138,795
Exclude financial firms (SIC code 6000-6999)	110,694
Require non-missing earnings news (two-day earnings announcement returns and forecast error)	91,693
Require 1. share price at the end of the quarter to be at least $1; 2. non-missing values for control variables that explain variation in returns (BETA, SIZE, BTM, and MOM11); 3. non-missing values for idiosyncratic return volatility and intraday mid-quote return variance; and 4. non-missing value for earnings volatility.	82,582
Require non-missing values for OFFEXCH calculated using Daily TAQ data.	82,502
Final sample from 2009Q1 to 2018Q2	*82,502*

Panel B: Data selection for the tick size pilot sample	Firms/Firm-quarters remaining	
	Control (SEC Test G2)	Treatment (SEC Test G3)
CRSP common stocks included in Tick Size Pilot Program test groups two (G2) and three (G3) as of October 2016, with daily quote and trade data before being delisted or rolled back into the tick size pilot control group.	361	368
Exclude firms that have more than 50% of trading days with less than 20 trades per day in the two-year windows before and after the implementation of the pilot program, following Rindi and Werner (2019).	321	337
Require 1. Each trading day to have at least 20 trades	317	333

2. A minimum of 30 trading days in both the two-year window before and the two-year window after the implementation of pilot program		
Firms available for liquidity analyses (daily-frequency)	*317*	*333*
Firm-quarters from 2014Q3 to 2018Q2 from sample above that satisfies the following requirements: 1. earnings announcement date is no more than 92 calendar days after fiscal quarter end; and 2. earnings announcement date is at least 30 trading days after previous quarterly earnings announcement.	4,570	4,659
Require 1. non-missing two-day earnings announcement returns; 2. non-missing values for control variables that explain variation in returns (BETA, SIZE, BTM, and MOM11); 3. non-missing values for idiosyncratic return volatility and intraday mid-quote return variance; and 4. each quarter post pilot program implementation has a corresponding quarter ending in the same calendar quarter before pilot program implementation.	3,636	3,370
Firm-quarters available for PEAD analyses (quarterly frequency)	*3,636*	*3,370*

Table 2: Descriptive statistics for our main sample (panel data)

This table reports descriptive statistics for key variables in our analysis. Panel A reports distributional statistics, and Panel B reports the Spearman (below the diagonal) and Pearson (above the diagonal) correlations among these variables. The sample includes 82,502 firm-quarters from 2009Q1 to 2018Q2. See Appendix for details of variables.

*, **, *** denote two-tailed p-values <0.10, <0.05, <0.01, respectively.

Panel A: Variable distributions

	Mean	Median	Standard deviation	First Quartile	Third Quartile
$SARET_{q+1}$	0.47%	-0.58%	22.44%	-10.38%	9.41%
FE	0.00%	0.05%	1.53%	-0.11%	0.27%
EARET	0.03%	-0.08%	8.31%	-4.28%	4.31%
OFFEXCH	31.31%	29.70%	9.20%	25.30%	35.57%
LOSS	0.31	0.00	0.46	0.00	1.00
FQ4	0.24	0.00	0.43	0.00	0.00
EVOL	-4.34	-4.45	1.17	-5.18	-3.58
ESPD	0.34%	0.14%	0.61%	0.07%	0.33%
DEP	25,100	11,826	314,513	6,180	23,407
IDVOL	-3.82	-3.83	0.54	-4.21	-3.46
VAR	-13.10	-13.21	1.37	-14.04	-12.33
BETA	1.19	1.15	0.48	0.86	1.47
SIZE	13.92	13.86	1.85	12.59	15.13
BTM	0.49	0.40	0.45	0.22	0.67
MOM11	16.17%	9.57%	55.56%	-14.42%	34.87%
NTRADES	6,809	2,608	12,000	876	7,606
TRSIZE	176	150	101	122	193

Table 2 (continued.)

Panel B: Correlation coefficients (Spearman below the diagonal, and Pearson above the diagonal)

	(1) $SARET_{q+1}$	(2) FE	(3) EARET	(4) OFFEXCH	(5) LOSS	(6) FQ4	(7) EVOL	(8) ESPD	(9) DEP	(10) IDVOL	(11) VAR	(12) BETA	(13) SIZE	(14) BTM	(15) MOM11
(1)		0.03***	0.04***	-0.05***	-0.02***	0.01**	0.00	-0.04***	0.02***	0.00	0.00	-0.01***	-0.01	0.02***	0.01***
(2)	0.04***		0.22***	-0.06***	-0.18***	-0.01**	-0.04***	-0.02***	0.01***	-0.04***	-0.06***	0.03***	0.06***	-0.08***	0.04***
(3)	0.04***	0.35***		-0.04***	-0.12***	0.01***	-0.03***	-0.02***	0.01*	-0.02***	-0.01***	0.00	0.01***	0.01*	0.00
(4)	-0.01***	-0.03***	-0.04***		0.39***	0.03***	0.40***	0.55***	-0.34***	0.52***	0.54***	-0.03***	-0.53***	0.03***	0.00
(5)	-0.06***	-0.16***	-0.12***	0.37***		0.02***	0.46***	0.39***	-0.28***	0.48***	0.45***	0.15***	-0.38***	0.03***	-0.11***
(6)	0.01***	-0.01***	0.01***	0.03***	0.02***		0.00	0.02***	0.00	-0.02***	0.01***	0.01***	0.00	0.00	0.05***
(7)	-0.05***	0.03***	-0.03***	0.37***	0.45***	0.00		0.42***	-0.30***	0.57***	0.46***	0.18***	-0.42***	-0.07***	0.02***
(8)	0.01	-0.07***	-0.01***	0.50***	0.26***	0.01***	0.27***		-0.77***	0.41***	0.61***	0.05***	-0.59***	0.19***	-0.11***
(9)	-0.02***	0.05***	-0.01*	-0.32***	-0.27***	0.00	-0.28***	-0.45***		-0.49***	-0.63***	-0.01***	0.82***	-0.22***	0.10***
(10)	-0.07***	0.03***	-0.03***	0.49***	0.47***	-0.01***	0.58***	0.67***	-0.52***		0.69***	0.28***	-0.68***	0.11***	0.00
(11)	-0.05***	0.00	-0.02***	0.51***	0.42***	0.02***	0.49***	0.85***	-0.69***	0.76***		0.17***	-0.76***	0.18***	-0.09***
(12)	0.01***	0.01***	0.00	-0.06***	0.16***	0.01***	0.18***	-0.23***	-0.01***	0.29***	0.10***		-0.03***	0.03***	0.07***
(13)	0.05***	0.01***	0.02***	-0.51***	-0.39***	0.00	-0.43***	-0.93***	0.84***	-0.69***	-0.81***	-0.04***		-0.28***	0.22***
(14)	0.00	0.02***	0.00	-0.05***	0.10***	-0.01*	-0.02***	0.21***	-0.24***	0.16***	0.21***	0.02***	-0.29***		-0.27***
(15)	0.04***	0.03***	0.01***	-0.07***	-0.20***	0.05***	-0.10***	-0.18***	0.19***	-0.20***	-0.23***	0.00	0.11***	-0.30***	

Table 3: Relation between off-exchange trading (OFFEXCH) and liquidity

Panel A reports results for panel regressions examining the relation between off-exchange trading (OFFEXCH) and liquidity, measured by effective bid-ask spread (ESPD) and dollar depth at NBBO (DEP). Regressions are estimated on the main sample of 82,502 firm-quarters from 2009Q1 to 2018Q2. All independent variables are ranked into deciles by calendar quarter and assigned values between -0.5 (lowest decile) and 0.5 (highest decile). t-statistics are based on standard errors clustered by both firms and quarters. Panel B reports OLS regression results of the following model for firm-day observations in the Tick Size Pilot sample: $Y_{i,t} = TREAT_{i,t} * POST_{i,t} +$ *Firm Fixed Effects* + *Date Fixed Effects* + $v_{i,t}$, where $Y_{i,t}$ is the percentage of off-exchange trading (OFFEXCH) or a liquidity measure. *TREAT* is an indicator variable equal to 1 if a stock belongs to the treatment group (SEC test group 3), and 0 if a stock belongs to the control group (SEC test group 2). *POST* is an indicator variable equal to 1 if the trading day is from the two-year window after the stock is phased into the SEC pilot program. The Tick Size Pilot sample includes 603,991 firm-days from October 2014 to September 2018. See Appendix for details of variables.
*, **, *** denote two-tailed p-value <0.10, <0.05, <0.01, respectively.

Panel A: Relation between OFFEXCH and market liquidity in the main sample

	(1) Ln(ESPD)	(3) Ln(DEP)
OFFEXCH	0.164***	-0.193***
	31.67	*-26.65*
NTRADES	-1.488***	0.900***
	-157.95	*68.56*
TRSIZE	0.228***	0.973***
	29.47	*90.41*
VAR	0.975***	-0.387***
	147.2	*-41.87*
PRC	-0.459***	0.477***
	-38.38	*28.59*
SIZE	-0.485***	1.038***
	-29.64	*45.55*
Firm Fixed Effects	*Yes*	*Yes*
Date Fixed Effects	*Yes*	*Yes*
Adj. R^2	95.80%	88.80%

Panel B: Impact of Tick Size Pilot on the level of off-exchange trading and market liquidity

	OFFEXCH	Ln(ESPD)	Ln(DEP)
TREAT*POST	-0.126***	-0.044***	0.091***
	-203.25	*-16.18*	*29.79*
Firm Fixed Effects	*Yes*	*Yes*	*Yes*
Date Fixed Effects	*Yes*	*Yes*	*Yes*
Adj. R^2	37%	73%	64%

Table 4: Relation between off-exchange trading (OFFEXCH) and post-earnings announcement drift (PEAD) in main sample

Panels A and B report results for panel regressions predicting next quarter's size-adjusted returns ($SARET_{q+1}$) based on earnings surprise measured as earnings announcement return (EARET) and analyst forecast error (FE), respectively. The interaction term between earnings surprise and off-exchange trading (OFFEXCH) estimates how PEAD (delayed price response per unit of earnings surprise) varies with OFFEXCH. All independent variables are ranked into deciles by calendar quarter and assigned values between -0.5 (lowest decile) and 0.5 (highest decile). Panel B includes all control variables considered in Panel A, but some coefficient estimates are not tabulated for brevity. The sample includes 82,502 firm-quarters from 2009Q1 to 2018Q2. t-statistics are based on standard errors clustered by both firms and quarters. See Appendix for details of variables. *, **, *** denote two-tailed p-value <0.10, <0.05, <0.01, respectively.

Panel A: Relation between OFFEXCH and PEAD for earnings surprise = EARET.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
EARET	0.026^{***}	0.022^{***}	0.029^{***}	0.030^{***}	0.029^{***}	0.030^{***}
	5.53	*4.81*	*6.11*	*6.21*	*6.12*	*6.16*
EARET*OFFEXCH		0.100^{***}	0.095^{***}	0.062^{***}	0.062^{***}	0.065^{***}
		9.88	*9.96*	*5.59*	*5.58*	*5.47*
EARET*LOSS			-0.008	-0.013^{*}	-0.013^{*}	-0.012
			-0.98	*-1.73*	*-1.69*	*-1.55*
EARET*FQ4			-0.026^{***}	-0.026^{***}	-0.026^{***}	-0.026^{***}
			-3.86	*-3.87*	*-3.88*	*-3.89*
EARET*EVOL			0.021^{***}	0.011	0.011	0.014^{*}
			2.60	*1.42*	*1.39*	*1.79*
EARET*ESPD				0.071^{***}	0.058^{***}	0.063^{***}
				6.35	*3.86*	*3.91*
EARET*DEP					-0.017^{*}	-0.017^{*}
					-1.73	*-1.79*
EARET*IDVOL						-0.014
						-1.05
OFFEXCH		-0.003	-0.001	-0.002	0.001	0.004
		-0.35	*-0.13*	*-0.29*	*0.19*	*0.77*
LOSS			-0.007	-0.006	-0.006	-0.005
			-1.28	*-1.24*	*-1.22*	*-1.14*
FQ4			0.004	0.004	0.004	0.004
			1.02	*1.03*	*1.03*	*1.02*
EVOL			0.001	0.001	0.002	0.005
			0.29	*0.33*	*0.55*	*1.28*
ESPD				0.013	0.013	0.014
				1.42	*1.40*	*1.55*
DEP					-0.024^{***}	-0.023^{***}
					-3.11	*-2.98*

IDVOL						-0.013
						-1.38
VAR						
BETA	0.003	0.003	0.004	0.004	0.004	0.007
	0.24	*0.25*	*0.37*	*0.31*	*0.32*	*0.67*
SIZE	-0.006	-0.009	-0.010	0.002	0.024**	0.019
	-0.95	*-1.41*	*-1.48*	*0.17*	*1.96*	*1.32*
BTM	0.001	0.000	-0.001	-0.001	0.000	-0.001
	0.07	*-0.05*	*-0.13*	*-0.10*	*-0.04*	*-0.10*
MOM11	0.011	0.011	0.010	0.009	0.009	0.009
	1.16	*1.11*	*1.01*	*0.98*	*0.92*	*0.92*
INTERCEPT	0.005*	0.005**	0.006**	0.006**	0.006**	0.006**
	1.83	*1.98*	*2.22*	*2.16*	*2.15*	*2.02*
Adj. R^2	0.16%	0.36%	0.40%	0.46%	0.49%	0.50%

Panel B: Relation between OFFEXCH and PEAD for earnings surprise = FE.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
FE	0.023***	0.016***	0.027***	0.024***	0.025***	0.025***
	5.35	*3.99*	*6.36*	*5.87*	*5.89*	*6.18*
FE*OFFEXCH		0.061***	0.072***	0.034***	0.037***	0.040***
		6.34	*7.70*	*2.97*	*3.25*	*3.55*
FE*LOSS			-0.006	-0.011	-0.011	-0.010
			-0.81	*-1.47*	*-1.48*	*-1.32*
FE*FQ4			-0.035***	-0.035***	-0.035***	-0.035***
			-7.07	*-6.97*	*-6.94*	*-6.93*
FE*EVOL			-0.020**	-0.028***	-0.028***	-0.023**
			-2.22	*-3.13*	*-3.13*	*-2.47*
FE*ESPD				0.074***	0.060***	0.066***
				5.80	*3.48*	*3.88*
FE*DEP					-0.016	-0.016
					-1.05	*-1.05*
FE*IDVOL						-0.018
						-1.32
Controls	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Adj. R^2	0.16%	0.24%	0.30%	0.37%	0.42%	0.44%

Table 5: Impact of Tick Size Pilot Program on post-earnings-announcement-drift

Panel A (C) confirms the presence of PEAD by estimating the following OLS regression for firm-quarter observations in the Tick Size Pilot (Placebo) sample: $SARET_{i,q+1} = SUR_{i,q} + BETA_{i,q} + SIZE_{i,q} + BTM_{i,q} + MOM11_{i,q} + v_{i,q}$, where SUR is earnings surprise defined as forecast error (FE) or earnings announcement return (EARET). To investigate if a plausibly exogenous shock to OFFEXCH affects PEAD, the results in Panel B (D) provide OLS regression estimates from the following model for firm-quarter observations in the Tick Size Pilot (Placebo) sample: $SARET_{i,q+1} = SUR_{i,q} + TREAT_{i,q}*POST_{i,q} + \mathit{Firm\ Fixed\ Effects} + \mathit{Date\ Fixed\ Effects} + SUR_{i,q}*TREAT_{i,q}*POST_{i,q} + SUR_{i,q}*\mathit{Firm\ Fixed\ Effects} + SUR_{i,q}*\mathit{Date\ Fixed\ Effects} + BETA_{i,q} + SIZE_{i,q} + BTM_{i,q} + MOM11_{i,q} + v_{i,t}$. *TREAT* is an indicator variable that equals 1 (0) if the firm belongs to the SEC test group 3 (group 2), representing the treatment (control) group that experienced a decline (increase) in OFFEXCH. For the Tick Size Pilot sample, the dummy variable *POST* equals 1 for quarters within 2016Q3 – 2018Q2 (i.e. the pilot window), and 0 for quarters within 2014Q3 – 2016Q2 (i.e., the pre-pilot window). For the Placebo sample, *POST* equals 1 for quarters within 2014Q3 – 2016Q2, and 0 for quarters within 2012Q3 – 2014Q2. The Tick Size Pilot sample includes 7,006 firm-quarters from 2014Q3 to 2018Q2, and the Placebo sample includes 6,210 firm-quarters from 2012Q3 to 2016Q2. All independent variables are ranked into deciles by calendar quarter and assigned values between -0.5 (lowest decile) and 0.5 (highest decile).

*, **, *** denote two-tailed p-value <0.10, <0.05, <0.01, respectively. See Appendix for details of variables.

Panel A: Post-earnings-announcement-drift in the Tick Size Pilot sample

	SUR=EARET	SUR=FE
SUR	0.027***	0.015
	3.61	*1.64*
Controls	*Yes*	*Yes*
# Obs.	7,006	6,006
Adj. R^2	0.44%	0.26%

Panel B: Impact of Tick Size Pilot on post-earnings-announcement-drift in the Tick Size Pilot sample

	SUR= EARET	SUR= FE
TREAT*POST	-0.014	0.126
	-0.12	*1.06*
SUR*TREAT*POST	-0.070**	-0.003
	-2.27	*-0.08*
Firm Fixed Effects	*Yes*	*Yes*
Quarter Fixed Effects	*Yes*	*Yes*
SUR*Firm Fixed Effects	*Yes*	*Yes*
SUR*Quarter Fixed Effects	*Yes*	*Yes*
Controls	*Yes*	*Yes*
# Obs.	7,006	6,006
Adj. R^2	26%	27%

Panel C: Post-earnings-announcement-drift in the Placebo sample

	SUR=EARET	SUR=FE
SUR	0.038***	0.032***
	5.37	*4.36*
Controls	*Yes*	*Yes*
# Obs.	6,210	5,261
Adj. R^2	2%	2%

Panel D: Impact of Tick Size Pilot on post-earnings-announcement-drift in the Placebo sample

	SUR= EARET	SUR= FE
TREAT*POST	0.188	0.144
	1.48	*1.19*
SUR*TREAT*POST	0.035	0.022
	1.21	*0.70*
Firm Fixed Effects	*Yes*	*Yes*
Quarter Fixed Effects	*Yes*	*Yes*
SUR*Firm Fixed Effects	*Yes*	*Yes*
SUR*Quarter Fixed Effects	*Yes*	*Yes*
Controls	*Yes*	*Yes*
# Obs.	6,210	5,261
Adj. R^2	20%	24%

Table 6: Relation between change in off-exchange trading at earnings announcement and PEAD

This table reports results for panel regressions predicting next quarter's size-adjusted returns ($SARET_{q+1}$) based on earnings surprise (SUR) measured as analyst forecast error (FE) and earnings announcement return (EARET). To avoid potential mechanical relations with $SARET_{q+1}$) the full specification in column (6) in Panels A and B of Table 4 is based on pre-announcement levels of average daily levels of OFFEXCH, ESPD, and DEP, rather than corresponding levels during the announcement window. To investigate whether any mechanical relation exists, we add to the original specification the following changes in the three measures between the pre-announcement and earnings announcement windows: $\Delta OFFEXCH_{EA}$, $\Delta ESPD_{EA}$, and ΔDEP_{EA}. *Control* variables include LOSS, FQ4, EVOL, and IDVOL. *Control2* variables include BETA, SIZE, BTM, and MOM11. All independent variables are ranked into deciles by calendar quarter and assigned values between -0.5 (lowest decile) and 0.5 (highest decile). Main effects of variables interacted with earnings surprise (SUR) are included in the models. The sample includes 82,502 firm-quarters from 2009Q1 to 2018Q2. t-statistics are based on standard errors clustered by both firms and quarters. See Appendix for details of variables.

*, **, *** denote two-tailed p-value <0.10, <0.05, <0.01, respectively. See Appendix for details of variables.

	SUR = EARET	SUR = FE
SUR	0.028***	0.025***
	5.51	*6.13*
SUR*OFFEXCH	0.068***	0.045***
	5.39	*3.92*
SUR*ESPD	0.070***	0.072***
	4.20	*4.37*
SUR*DEP	-0.009	-0.008
	-0.89	*-0.56*
SUR*$\Delta OFFEXCH_{EA}$	0.010	0.020**
	0.99	*2.11*
SUR*$\Delta ESPD_{EA}$	0.006	-0.006
	0.59	*-0.52*
SUR*ΔDEP_{EA}	0.024**	0.032***
	2.15	*3.51*
∑SUR*Control	*Yes*	*Yes*
Main effects & Controls	*Yes*	*Yes*
Adj. R^2	0.52%	0.42%